

The ecology of financial markets: From analogy to application

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Abstract

This dissertation is motivated by the 2007-2009 financial crisis and the failure of the mainstream economic methodology to detect the increased fragility of the pre-crisis financial system. I explore the viability of alternative approaches focusing on the methodological blind spots that were revealed by the financial crisis. In particular, I focus on ecological approaches since economics and ecology share many phenomenological similarities but harbor many opposing methodological doctrines, which make them complementary. The collection of projects presented here is my attempt at facilitating crosspollination between the two disciplines dealing with similar problems. The first project considers the connections between ecology and economics, and provides a historical account of how analogical models inspired by different research paradigms led to the development of two contrasting methodological perspectives in economics, the *classical physics worldview* and the *life sciences worldview*. I find that the recent financial crisis precipitated a shift in economic methodology towards approaches inspired by life sciences. In the remaining two projects I apply ecological models to finance by combining network approaches with agent-based simulations to study contagion in banking systems. In the first simulation study I explore the impact of uncertainty on the stability of banking networks and show that information asymmetries lead to a striking increase in the risk of system collapse after a financial shock. In the second simulation study I investigate the relationship between concentration and resilience in banking systems. I find, counterintuitively, that an increase in concentration can be beneficial for system stability in certain conditions. Specifically, when concentration is decoupled from inequality, its increase can improve system resilience. Taken together, this thesis shows that ecological approaches can be fruitfully used to illuminate economic problems.

Keywords: financial crisis, paradigm shift, physics, life sciences, ecology, network, simulation, resilience

Zusammenfassung

Diese Dissertation ist motiviert durch die Finanzkrise im Jahre 2007-2009 und das Versagen der ökonomischen Methodologie die gestiegene Fragilität des Finanzsystems vor der Krise zu erkennen. Ich untersuche die Nützlichkeit von alternativen Ansätzen und fokussiere dabei auf methodologischen Defizite des Standardansatzes, die sich im Zuge der Finanzkrise offenbart haben. Insbesondere fokussiere ich auf ökologische Ansätze, da die Ökonomie und die Ökologie ähnliche phänomenologische Gemeinsamkeiten haben und dennoch viele gegensätzliche methodologische Doktrinen beherbergen, so dass sie sich ergänzen können. Die Ansammlung von Studien, die ich hier präsentiere, ist mein Versuch die Kreuzbestäubung der zwei Disziplinen, die sich mit ähnlichen Problemen auseinander setzen, zu erleichtern. Die erste Studie betrachtet die Verbindungen zwischen Ökologie und Ökonomie und setzt sich mit der historischen Fragestellung auseinander wie Analogie-Modelle, inspiriert durch unterschiedliche Forschungsparadigmen, zu einer Entwicklung von zwei gegensätzlichen methodologischen Sichtweisen innerhalb der Ökonomie geführt haben: die Weltsicht der klassischen Physik und die Weltsicht der Lebenswissenschaften. Dabei finde ich, dass die Finanzkrise eine Veränderung in der ökonomischen Methodologie in Richtung von Ansätzen aus den Lebenswissenschaften verursacht hat. In den letzten zwei Studien wende ich ökologische Modelle auf die Finanzwissenschaft an, indem ich Netzwerk-Ansätze mit Agenten-basierten Simulationen kombiniere, um Contagion-Effekte in Bankensystemen zu studieren. In der ersten Simulationsstudie untersuche ich den Einfluss von Unsicherheit auf die Stabilität von Bankensystemen und finde, dass Informationsasymmetrien zu einem erstaunlichen Anstieg des Risikos eines Systemkollapses nach einem Finanzschock führen können. In der zweiten Simulationsstudie untersuche ich den Zusammenhang zwischen Konzentration und Resilienz von Bankensystemen. Ich finde, kontraintuitiv, dass ein Anstieg in Konzentration unter bestimmten Umständen für die Systemstabilität nützlich sein kann. Im Besonderen, wenn Konzentration von Ungleichheit entkoppelt ist, kann ihr Anstieg die Systemresilienz erhöhen. Zusammengefasst, zeige ich in dieser Arbeit, dass ökologische Ansätze fruchtbar gemacht werden können, um ökonomische Probleme zu beleuchten.

Schlüsselwörter: Finanzkrise, Paradigmenwechsel, Physik, Lebenswissenschaften, Ökologie, Netzwerk, Simulation, Resilienz

1. Introduction

The 2007-2009 financial crisis and the failure of economists to detect the increased fragility of the pre-crisis financial system, let alone anticipate the breakdown, sparked an intense public discussion among economists, scholars from other fields, and policy makers about the credibility of methodology used in mainstream economics (e.g. Cochrane, 2011; Haldane & Madouros, 2012; Krugman, 2009). According to critics, economic models are: too abstract and hard to relate to economic reality; reductionist and lacking the holistic perspective needed to integrate pieces of economic reality in a coherent whole; based on assumptions with no empirical support such as rationality, selfishness, or equilibrium. In this context, a variety of research programs practicing alternative approaches have claimed that their methods can provide a viable remedy. The question that naturally arises is: which of the offered alternatives is capable of dealing with the identified blind spots in mainstream methodology?

This work explores the possibility of applying methods from ecology, a discipline that shares many phenomenological similarities with economics, to the study of economic systems. Both ecology and economics are concerned with the interplay of many heterogeneous agents interacting in a non-random manner, often producing nonlinear effects, amplifications, and feedback loops. This is why, for instance, a synchronized behavior such as hoarding can be observed in both domains and is a common factor underlying collective dynamics in biological populations and financial markets. One can also find meaningful parallels between the two at the micro level: both humans and animals compete for market share or territory, form coalitions to survive or outperform other

groups, as well as make their living in their respective complex environments composed again of many interacting factors, from climate to market regulations.

At their very beginnings, economics and ecology were commonly recognized as disciplines devoted to studying the allocation of scarce resources. The reference of “ecology as the economy of nature” dates back to Carl Linnaeus in 1749 (Egerton, 2007), and also appears later in the first comprehensive definition of ecology proposed in 1870 by Ernst Heinrich Haeckel:

“By ecology we mean the body of knowledge concerning the economy of nature – the investigation of the total relations of the animal both to its inorganic and to its organic; including above all, its friendly and inimical relations with those animals and plants with which it comes directly or indirectly into contact – in a word, ecology is the study of all those complex interrelationships referred to by Darwin as the conditions of the struggle for existence.” (cited in Costanza, 1996, p. 978)

The two disciplines can also be defined in a complementary way: economics deals with the ecology of humans, with a focus on how they manage their affairs; whereas ecology covers the economy of the rest of nature that does not ordinarily include humans (Costanza, 1996). Furthermore, ecology and economics are both keenly interested in understanding the dynamics and stability of their respective systems. Yet, ecology and economics developed very different methodologies.

An early advocate of biologically oriented approaches in economics, Alfred Marshal, was explicit about the methodological difficulties he faced in building up an alliance between these two disciplines that are naturally connected:

“The Mecca of the economist lies in economic biology rather than in economic dynamics. But biological conceptions are more complex than those of mechanics; a

volume on Foundations must therefore give a relatively large place to mechanical analogies; and frequent use is made of the term 'equilibrium,' which suggests something of statical analogy." (Marshall, 1890/1920, p. 19)

A more general insight about methodological challenges arising from complexity comes from Warren Weaver (1948) who provided a systematic decomposition of scientific questions by distinguishing between problems of simplicity, disorganized complexity, and organized complexity. He provided examples to illustrate that methods that proved successful in dealing with problems of simplicity were ineffective with problems of disorganized and organized complexity. While the introduction of statistical approaches made a significant advance in dealing with problems of disorganized complexity, problems of organized complexity in which variables interact in a nonrandom manner still remained difficult to deal with. He explained that it was physics that initially started dealing with simple problems, while biology was naturally devoted to problems of organized complexity, given that problems of living organisms "are seldom those in which one can rigidly maintain constant all but two variables" (Weaver, 1948, p. 2).

The major scientific revolution, which introduced the Age of Enlightenment, was ushered in by a research paradigm that was successful in explaining "simple" physical phenomena such as the interaction of two moving bodies, the trajectory of falling objects, or celestial motions. The advent of mechanical physics had a huge impact in science and methods that proved efficient in the physical domain soon became exemplars for research in other fields. These events found economics and ecology standing on different intellectual traditions. While the study of economic issues was deeply rooted in moral philosophy mostly concerned with theory (e.g. Adam Smith, 1723–1790), ecological phenomena were investigated by scholars within the biological tradition devoted to empirical research (e.g.

Carl Linnaeus, 1707–1778). Therefore, the success of Newtonian physics had different impacts on the two nascent disciplines: the study of economic problems was taken over by engineers and physicists such as Leon Walras (1834–1910), Vilfredo Pareto (1848–1923), William Stanley Jevons (1835–1882), and Alfred Marshal (1842–1924), who set the methodological foundations of the field; whereas ecology remained in hands of zoologist, botanists, physicians, geographers, and explorers such as Alexander von Humboldt (1769–1859), Alfred Russel Wallace (1823–1913), Karl Möbius (1825–1908), and Eugenius Warming (1841–1924). The former used philosophical theorizing to link physical and economic phenomena, whereas the latter stuck to observation and made most of their contribution not in theory but rather in the collection, classification, and description of ecological phenomena.

In the given context, the difference in the intellectual cultures of economics and ecology produced a vast discrepancy in established worldviews and methodologies that shaped the two fields. The “simplified” worldview borrowed from Newtonian physics led to the development of foundational assumptions in economics such as rationality, selfishness, equilibrium, and the independence of economic interactions (Colander, Holt, & Rosser, 2004; Weintraub, 2007). For instance, it took more than a century and the establishment of a separate branch in the field, behavioral economics, to place importance on observations and show that the assumptions of rationality and selfishness cannot be empirically supported. On the other hand, ecology was strongly influenced by Charles Darwin and thus interested in the evolution of biological populations, as well as out-of-equilibrium dynamics. Ecologists were also deeply interested in interspecies interactions and constructed food webs, integrating them in a holistic way with other environmental factors.

Weaver's (1948) decomposition of scientific problems helped with the understanding of the important reasons for the divergence of the doctrinal positions and methodology of the two fields. However, it begets the question: Which of Weaver's categories do most of economic and ecological phenomena belong? Reminiscent of Weaver's argument that different kinds of complexity require different treatments, a classic paper by Philip Warren Anderson (1972) argued that each successive level of complexity often necessitates the invention of novel methodological approaches. Anderson gave the example of how the fundamental laws postulated by reductionistic physics, such as particle physics, have a very limited application in the domain of solid-state physics, which deals with many elementary entities well understood in particle physics. He made the general argument that "At each stage [of complexity] entirely new laws, concepts, and generalizations are necessary, requiring inspiration and creativity to just as great a degree as in the previous one. Psychology is not applied biology, nor is biology applied chemistry" (P. W. Anderson, 1972, p. 393). Another example he gave was that quantum physics and relativity theory provide laws for different aspects of physical reality, which can be successfully applied in their respective domains despite our difficulties to reconcile them.

Returning to the question posed earlier: where do economic and ecological phenomena belong in Weaver's taxonomy of complexity? According to Anderson (1972), who constructed a hypothetical hierarchy of sciences, social sciences reside at the highest level of complexity. While economics is clearly a social science, there are many indications that ecological phenomena also belong to very high levels of the hierarchy of complexity. Ecologists are concerned about problems that include organisms, their social interactions, as well as their adaptation to the non-living habitat, such as landscape, soil type, or climate. For instance, understanding the stability of relatively simple coastal, estuarine, or savanna

ecosystems requires a comprehensive analysis of the number of often intricately interconnected factors (Costanza, Kemp, & Boynton, 1993; Van Langevelde et al., 2003). Similarly, economics studies the variety of human economic interactions taking into account different aspects of the context in which they take place. Furthermore, economics is interested in the ecological aspects of human activity, and conversely modern ecology also incorporates humans in the study of socio-ecological systems (Berkes & Folke, 1998; Holling, 2001), which can make existing ecological problems even more complex (Liu et al., 2007). Therefore, a substantial portion of phenomena from both fields consists of a number of factors acting together simultaneously to shape the resulting patterns observed in those phenomena.

Even though the described phenomenological similarities would suggest corresponding methodological similarities, many approaches that have been successfully applied in ecology are still not common in mainstream economics. Agent-based models in combination with network approaches, for instance, are common tools that provide a framework for studying the structure of interactions between species in an ecosystem (Grimm et al., 2006; Janssen, Schoon, Ke, & Börner, 2006), but are still scarcely used in mainstream economics. Nevertheless, there are some good examples of the use of these models in finance, even though they are often applied by researchers from other disciplines (e.g. physicists, or epidemiologists) and have yet to gain acceptance from the mainstream. The collaboration among the adherents of the ecological view in economics eventually led to the establishment of the International Society of Ecological Economics, and the journal *Ecological Economics* published its first issue in 1988 (Costanza, 1996). Perhaps the most influential research program that advocates approaches in line with those from modern ecology is that of *complex systems*, commonly associated with the Santa Fe Institute for

Complex Systems founded in 1984. While ecosystems are typical examples of complex systems, the paradigm of complex systems is more abstract and covers a variety of physical and biological phenomena that share characteristics such as nonlinear interactions, self-organization, emergence, feedback loops, far-from-equilibrium dynamics, and hierarchical organization. Within this paradigm, a special kind of complex systems, complex adaptive systems, are recognized as distinctly relevant for a better understanding of the resilience of ecological and economic systems. Complex adaptive systems are distinguished by their particular ability to memorize, learn, and adapt to various environmental changes (Holland, 1992b), features also observed in ecological and economic phenomena (Di Matteo, Aste, & Dacorogna, 2005; Lo, 1991).

As a result of these dispersed efforts, after the 2007–2009 financial crisis ecological insights have been more commonly used to understand the resilience of financial markets (Battiston et al., 2016; May, Levin, & Sugihara, 2008). Some examples of concepts from ecology and complex systems that are becoming increasingly frequent in the finance literature are tipping points (Scheffer et al., 2012), warning signs (Scheffer et al., 2009), relationships between the structural properties of system and its resilience (e.g. too central to fail concept, Thurner & Poledna, 2013), and the use of agent-based simulations as tools for designing financial regulations (Klimek, Poledna, Farmer, & Thurner, 2015; Poledna & Thurner, 2014).

The collection of projects presented in this dissertation is my attempt at facilitating crosspollination between the two disciplines dealing with similar problems. The dissertation contains three chapters: the first chapter considers the conceptual connections between ecology and economics, but also the application of other influential analogical models in

economics; the second and third chapters are applications of ecological models in studying financial markets.

The first chapter provides a historical account of how different analogical models, such as those from mechanistic physics, evolutionary biology and ecology, inspired the modeling of economic phenomena. Following Gerald Holton's (1988) thematic analysis I identify methodological themata that characterize each of those analogical models. I further argue that analogies have led to the development of two contrasting methodological perspectives in economics, the *classical physics worldview* and the *life sciences worldview*, and show that they are characterized by distinctive and often incompatible thematic positions. For instance, analogies from classical mechanics can be associated with thematic positions such as reductionism, equilibrium, and certainty. In contrast, analogies from life sciences based on concepts of evolution, ecology, and complex adaptive systems suggest opposite thematic positions such as holism, discontinuities, and uncertainty. While analogies from physics were dominant in the mainstream approach throughout the era of classical and neoclassical economics and analogies from the life sciences had minor influence, there is little evidence about the current state of the field. With this in mind, I speculate that the 2007–2009 financial crisis provided an intellectual stimulus to economists to reconsider their methodology given the amount of public criticism that arose in the aftermath of the crisis. I use survey and keyword analysis to compare methodological themata employed in papers produced at five leading economics departments before and after the crisis. I find some early indications of paradigm change and openness of economic methodology toward more organic analogies: a higher involvement of holistic at the expense of reductionist approaches, increased use of complex adaptive systems as a suitable framework for policy-making recommendations, wider adoption of bounded

rationality as a model of economic agents, as well as higher occurrence of keywords such as complexity, novelty, discontinuity, and networks in the papers written after the crisis.

In the second chapter, I study the role of information and confidence in the spread of financial shocks through interbank markets. Confidence in financial institutions has only recently been introduced in computational models studying the resilience of financial networks (Arinaminpathy, Kapadia, & May, 2012). However, so far it has been assumed that all agents have complete information about the system. In this study I add realism to a model of interbank markets by introducing uncertainty into what banks know about other banks. In my model, information spreads through the lending network and the quality of information depends on the proximity of the information source. Instead of having complete information, banks receive information that is delayed, noisy, or local. This affects their confidence and the resulting lending decisions. I show that introducing uncertainty leads to a substantial increase in systemic risk after an idiosyncratic bank failure. In contrast, when the same shock is distributed among multiple smaller banks, uncertainty mitigates the impact of the shock. The consequences of a large bank's failure are the most difficult to predict. This chapter demonstrates the need for a better understanding of the role of information asymmetries in systemic risk in financial networks.

The last chapter investigates the role of concentration in the resilience of banking systems. Since the 2007–2009 financial crisis, mounting evidence suggests that failures of large banks represent a major risk for the resilience of banking networks. This finding is widely used to link the increasing concentration of financial markets with an increase in their fragility. However, the same argument can easily result in the mistaken idea that any market change associated with an increase in concentration also amplifies systemic risk. In this study I apply stress tests to both hypothetical and empirically calibrated banking

networks to observe how various bank-size distributions affect systemic risk. I find that, analogous to the resilience of ecosystems, no single property of banking networks could explain the probability of systemic failure. I quantify *concentration* in terms of the Herfindahl–Hirschman index and also identify an additional indicator, *inequality*, measured by Rao’s quadratic entropy, which is important for understanding the concentration–resilience relationship. I find, counterintuitively, that an increase in concentration is beneficial when it is not followed by an increase in inequality. Similarly, a decrease in concentration becomes harmful when it is not followed by a decrease in inequality. Mergers of large banks increased, whereas mergers of small banks decreased systemic risk. Splitting of large banks was also effective in reducing systemic risk if splitting was not overdone to the extent that it resulted in too many small banks. These results provide a guideline that can be applied to frequent issues that regulators face, such as bank mergers.

Taken together, the work in this thesis shows that ecological approaches can illuminate important economic phenomena, including the effects of uncertainty, concentration, and inequality on the resilience of banking systems. More broadly, the thesis shows that there are systematic methods that can help in selecting analogical models well suited to the problems of interest. Unlike Marshal who could not afford to follow his own intuition, present-day researchers have the opportunity to take advantage of various methodological advances that put them in a better position to deal with complex problems. For instance, the development of conceptual foundations such as complex systems, analytical techniques such as network approaches and agent-based simulations, as well as various technological innovations such as widely accessible and increasingly powerful computational devices provides a strong foundation for the future research that does not need to compromise its way.

2. The 2007-2008 Financial Crisis and Paradigm Shift: A Study on Analogies in the History of Economics^{*}

Abstract. The recent 2007–2009 financial crisis has sparked discussion on whether failure of economists to detect the increased fragility of the pre-crisis financial system can be attributed to their supposedly outdated models that still have a strong neoclassical spirit (Arthur, 2014; Cochrane, 2011; Colander, 2010; Colander et al., 2009; Farmer & Geanakoplos, 2009; Haldane & Madouros, 2012; Krugman, 2009). Inspired by this discussion, we sought to answer two questions: (i) To what extent does contemporary mainstream economic methodology still hinge on classical physics? (ii) Has the experience of the financial crisis encouraged the use of alternative analogies in mainstream economic methodology? To answer these questions, we conducted a systematic analysis of analogies used throughout the history of economics. In line with Gerald Holton’s thematic analysis (1988), we argue that analogies have led to the development of two contrasting methodological perspectives in economics, the classical physics worldview and the life sciences worldview, and show that they are characterized by distinctive and often incompatible thematic positions. For instance, analogies from classical mechanics can be associated with thematic positions such as reductionism, equilibrium, and certainty. In contrast, analogies from life sciences based on concepts of evolution, ecology, and complex adaptive systems suggest opposite thematic positions such as holism, discontinuities, and uncertainty. While analogies from physics were dominant in the mainstream approach throughout the era of classical and neoclassical economics and analogies from the life sciences had minor influence, there is little evidence about the current state of the field. To assess the current situation and test if the 2007–2009 financial crisis provided an intellectual stimulus to economists to reconsider their methodology, we used survey and keyword analysis to compare methodological themata employed in papers produced at five leading economics departments before and after the crisis. We found some early indications of paradigm change and openness of economic methodology toward more organic analogies: a higher involvement of holistic at the expense of reductionist approaches, increased use of complex adaptive systems as a suitable framework for policy-making recommendations, wider adoption of bounded rationality as a model of economic agents, as well as higher occurrence of keywords such as complexity, novelty, discontinuity, and networks in the papers written after the crisis.

^{*} I collaborated on a version of this chapter together with Mirta Galesic and Gerd Gigerenzer.

Introduction

The founding father of economics, Adam Smith, explicitly expressed his deep admiration for Isaac Newton's work:

"The superior genius and sagacity of Sir Isaac Newton...made...the greatest and most admirable improvement that was ever made in philosophy, when he discovered, that he could join together the movements of the Planets by so familiar a principle of connection, which completely removed all the difficulties the imagination had hitherto felt in attending to them." (Smith, 1795/1822, p. 71)

Newton's methods affected Smith's standpoint on not only the order of the material world, but also human nature (Alvey, 1999). The mechanistic spirit of Smith's *The Wealth of Nations* reveals a strong influence of Newton's *Principia* (Lowe, 1975; Sebba, 1953). The influence extended to Leon Walras: "The necessary and sufficient reason for the equilibrium of the economic world, just as the universal attraction based directly on the mass and inversely upon the square of the distance is the reason for the equilibrium of the astronomical world" (Walras, 1927/1987, p. 320). Newtonian physics became the analogy for classical and later neoclassical economics.

Just as in science in general (Holton, 1988), analogical reasoning is important in economics and finance. Real-world economic systems are extremely complex, difficult to measure, and difficult to predict. As Knight (1921) pointed out, much of economic interaction is characterized by deep uncertainty that is hard or impossible to quantify but necessary to make a profit. In Binmore's (2009) terms, an economic system is a "large world," characterized by limited information and rapid change in the environment. Models of risk developed for "small worlds," where probabilities and outcomes are known, are not

necessarily successful in large worlds. Because of its complexity, the study of economics has relied on analogies from more familiar domains since the beginning. For instance, William Stanley Jevons (1871/1888) used a mechanical lever as a model for his theory of exchange. Similarly, a pendulum was the vehicle of Paul Samuelson's (1986, pp. 231–232) optimization model, and Irving Fisher (1892) developed a general equilibrium model of a three-consumer economy as a hydraulic machine, which was actually constructed (Brainard & Scarf, 2005). Random walk, a fundamental assumption of modern finance, was inspired by Fourier's model of thermal conduction within a material body (Mandelbrot & Hudson, 2010).

There is ample evidence that theories suggested by Smith's successors, such as Jevons, Walras, and Vilfredo Pareto, were strongly inspired by classical mechanics (Ingrao & Israel, 2000; Mirowski, 1989). Marginalism and general equilibrium theory, two classic examples, immediately became the main pillars of economic theory. It is generally accepted that the use of analogies from classical mechanics and thermodynamics had great consequences for the development of the field of economics. Yet, some authors have argued that the seeds of classical physics¹ are planted so deeply in the economic methodology that their influence on economic thinking and modeling is still significant within the so-called mainstream approach. This has become increasingly relevant since the recent 2007–2009 financial crisis that has sparked discussion on whether the failure of economists to detect the increased fragility of the pre-crisis financial system can be attributed to their supposedly outdated models that still have a strong neoclassical spirit (Arthur, 2014; Cochrane, 2011; Colander, 2010; Colander et al., 2009; Farmer &

¹ Here we adopt a narrower definition of classical physics that includes classical mechanics, classical electrodynamics, and classical thermodynamics but not special and general relativity, classical chaos theory, and nonlinear dynamics. In particular, our classical physics model includes economic interpretations of models of classical mechanics and thermodynamics.

Geanakoplos, 2009; Haldane & Madouros, 2012; Krugman, 2009). Inspired by this discussion, we set out to answer two questions: (i) To what extent does contemporary mainstream economic methodology still hinge on classical physics? (ii) Has the experience of the financial crisis encouraged the use of alternative analogies in the mainstream economic methodology?

To answer these questions, we conducted an analysis of analogies used throughout the history of economics. Borrowing from Thomas Kuhn's (1962) perspective on the cycle of scientific revolutions, we argue that analogies, as tools for coping with uncertainty and conceptualizing the unknown, will be discussed particularly often in the parts of Kuhn's cycle in which there is no established view of the world (*prescience*) or when there is low confidence in an established worldview (*crisis of the model*). Prescience is characterized by inventive mapping of analogies to the phenomena of interest and using them to develop initial methodological tools. In this period, analogies are easy to notice in the literature. In particular, early economists, such as Walras, Jevons, Pareto, and Alfred Marshal, did not hesitate to explicitly discuss analogies for their models and even included them in their textbooks. When a particular worldview and the corresponding methodological tools become widely accepted by the scientific community, the cycle reaches the period of *normal science*. In this period, the analogies that led to the development of the tools become invisible. Crisis of the model typically arrives with major scientific revolutions or events momentous for a particular field that raise wider awareness of the limitations of the established worldview and its underlying analogies; the analogies are revisited and alternatives are discussed. This analogical cycle of scientific revolutions suggests that our second question, whether the latest financial crisis brought changes to the economic methodology, could be answered affirmatively. Specifically, we explored whether the

greatest financial breakdown since the Great Depression has set off a crisis of the standard classical physics model, which should be indicated by the increased discussion of analogies. Since the discussion of thematic inspirations is absent from the “public science” (Holton, 1996), and there are no definite signs of an overt crisis, we looked for covert indications of change at the methodological level. We reasoned that if such indications were found, postcrisis economic methodology might have become more open to alternative analogies, which should be reflected in decreased use of analogies from classical physics and increased use of competing alternatives, primarily life sciences analogies. This, in turn, creates a context in which a *paradigm change* might occur.

To assess a possible change of analogical content in the economic methodology, we adopted Gerald Holton’s (1973/1988) thematic analysis. More than 40 years ago Holton introduced thematic analysis as a tool for exploring the thematic origins of scientific discoveries. A success or failure of scientific agendas, Holton argued, can be associated with thematic presuppositions—*themata* that guide scientific thinking. Themata are “highly motivating and general presuppositions or hypotheses that are not directly derivable from the phenomena and are not provable or falsifiable” (Holton, 1996, pp. 454–455). In this context, we classified the most influential analogical thematic concepts in economic thought according to the two principal worldviews: the classical physics worldview and the life sciences worldview. The worldviews are composed of various analogies, and other analogies that cannot be included in either of the two categories are discussed, as well (see Table 1). Not all themata are equally relevant for each analogical model, hence some of the cells in Table 1 are not defined (ND). Since our focus is on assessment of economic methodology, we paid special attention to *methodological themata* that are derived from respective thematic concepts. Methodological themata are basic methodological presuppositions that

serve as guiding ideas in designing a particular scientific inquiry. For instance, reductionism is a methodological presupposition that properties of a complex phenomenon can be deduced from the interaction of an arbitrarily small number of its fundamental parts. Methodological themata can often be represented as opposing dyads, such as reductionism/holism or certainty/uncertainty. In line with Holton's approach, we composed a *thematic map* based on these dual representations, that is, a set of methodological themata that can be used to characterize and contrast relevant thematic concepts. Take reductionism/holism and certainty/uncertainty as an example of a simple thematic map: Analogies from classical mechanics would be associated with the left end of the dyads (reductionism and certainty) and analogies from ecology would correspond to the opposite end (holism and uncertainty), as shown in Figure 1. In this framework our questions can be reformulated: (i) How far apart are thematic positions of contemporary mainstream economics and classical physics on our thematic map? (ii) Has the position of mainstream economics changed in the expected direction because of the financial crisis?

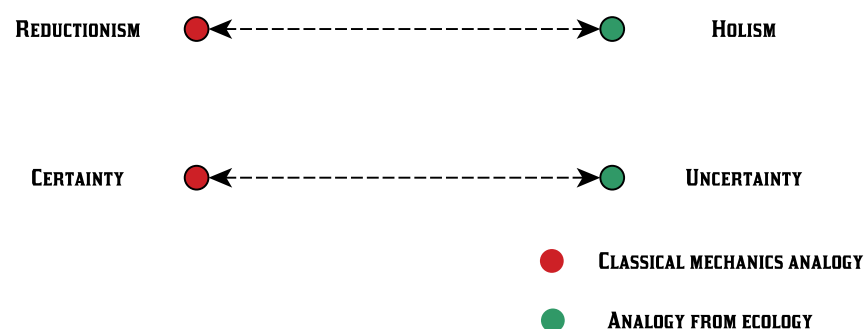


Figure 1. An example of a thematic map.

Table 1. Overview of the analogies and the corresponding methodological themata

Methodological thema	Analogical model						
	Classical physics worldview		Unclassified		Life sciences worldview		
	Mechanistic	Thermodynamic	Chaotic	Statistical	Evolutionary	Ecological	Complexity
1. Reduction	Strong reductionism	Strong reductionism	Holism	Holism	Holism	Holism	Holism
2. Isolation	Closed system	Closed system	ND	Closed or open system	ND	Open system	Open system
3. Reversibility	Reversible	Irreversible	ND	Irreversible	Irreversible	Irreversible	Irreversible
4. Dynamic tendency	Equilibrium	Equilibrium	Discontinuities	Equilibrium or discontinuities	Discontinuities	Discontinuities	Discontinuities
5. Linearity	Linear	Linear	Nonlinear	ND	Nonlinear	Nonlinear	Nonlinear
6. Determinism	Deterministic	Deterministic	Deterministic	Stochastic	Stochastic	Stochastic	Stochastic
7. Complexity	Simple	Simple	Complex	Simple or complex	Complex	Complex	Complex
8. Epistemological view	Certainty	Certainty	Uncertainty	Uncertainty	Uncertainty	Uncertainty	Uncertainty
9. Behavioral model	Rational actor	Rational actor	ND	ND	Bounded rationality	Bounded rationality	Bounded rationality
10. Stability concept	Engineering resilience	Engineering resilience	ND	ND	ND	Ecological resilience	Ecological resilience

Note. ND = Not defined.

Given that relatively little time has passed since the crisis and that the publication lead time of economic journals is quite long (Ellison, 2002), our study focused on working papers produced at five leading economics departments before and after the crisis. In particular, we contrasted papers that became publically available immediately before the crisis in 2006 with corresponding papers from 2013. To place the methodology of the papers on our thematic map, we employed two methods: a questionnaire study and a keyword study. In the questionnaire study we asked authors of the papers to assess to what extent certain methodological assumptions were reflected in their studies. In the keyword study, for the same corpus of papers, we counted occurrences of keywords that corresponded to different methodological themata. Our results suggest that on an absolute level, methodological presuppositions inherited from classical physics are still deeply entrenched in mainstream economics. On the other hand, signs of change in the methodology due to the crisis are moderate but present.

The rest of this paper is organized as follows. We start with a section addressing conceptual aspects of analogies, followed by a section presenting a historical overview of influential analogies for economics models (Table 1). The same section also deals with corresponding methodological themata and the construction of the thematic map. The last section provides details on the questionnaire and keyword studies, including the results. We end with a discussion of results.

Analogies

The terms analogy and metaphor are often used interchangeably (McCloskey, 1985; Mirowski, 1989). While both are used to make comparisons, analogies are usually characterized as more elaborate than metaphors. For instance, metaphors typically compare general features of objects from different domains (e.g., “the atom is a solar

system”), and analogies compare relationships between objects in one domain to corresponding relationships in another domain (e.g., “electrons circulating in the nucleus are like planets orbiting the sun”; Klahr & Leonard, 1994). According to the structure-mapping theory,² an analogy is “a mapping of knowledge from one domain (the base) into another (the target), which conveys that a system of relations that holds among the base objects also holds among the target objects” (Gentner, 1998).

Cognitive tools for uncertainty

Using analogies to understand and explain the unknown is prevalent in science. Their potential to generate creative ideas and fresh insights, particularly important for scientific discovery, is widely recognized by philosophers of science (Hesse, 1966; Kuhn, 1979; McCloskey, 1985), psychologists (Gentner et al., 1997; Holyoak & Thagard, 1996; Langley & Jones, 1988), and economists (Morgan, 2012). When faced with phenomena that are novel, difficult to observe, or very complex, scientists often use analogies from familiar domains (Dunbar, 1997). Maxwell was explicit: “Instead of using the analogy of heat, a fluid, the properties of which are entirely at our disposal, is assumed as the vehicle of mathematical reasoning.... The mathematical ideas obtained from the fluid are then applied to various parts of electrical science” (Maxwell, 1855/1990, p. 367). Similarly, Smith was also deeply aware of their importance: “The analogy, which...gives occasion to a few ingenious similitudes became the great hinge upon which every thing turned” (Smith, 1795/1822, p. 18).

More generally, people use analogies to interpret unfamiliar situations in everyday life. Analogical thinking is a cognitive tool specialized to deal with novelty and uncertainty

² Structure mapping is a theory of human processing of analogy and similarity (Gentner, 1983).

(Chan, Paletz, & Schunn, 2012). In the psychological literature this is recognized on many different levels. One of the most serious challenges in learning and problem-solving research is understanding how people act in novel environments. Thus, many general theoretical problem-solving frameworks integrate analogy as a strategy selection instrument in uncertain conditions. The heuristic-based information-processing models of Simon and Newell (1971) recognize analogy as an important strategy for searching in a problem space.³ Similarly, analogical mapping has been incorporated in Anderson's ACT-R cognitive architecture as a potential mechanism for constructing new production rules⁴ (J. R. Anderson, Fincham, & Douglass, 1997; Salvucci & Anderson, 2001).

The power and limitations of analogies

Analogies can be used to explain a new concept (pedagogical analogies), cast new light on a subject (heuristic analogies), or even import a novel way of thinking on a more fundamental level (constitutive analogies; Klammer & Leonard, 1994). Here we focus on constitutive analogies, which are often used to interpret an unknown domain (target) by borrowing a well-established model or a system of relationships from a more familiar scientific domain (source or base). An example is the use of evolutionary models to explain the emergence of new technologies, firms, and industries, as well as their development, progress, and extinction. For instance, the concept of natural selection among species is applied to modeling competition among firms. "In doing so, economists can be said to have 'chosen' the world of the model" (Morgan, 2012, p. 173).

³ Even some of the general problem-solving architectures fully rely on a broadly interpreted form of analogical reasoning (R. M. Jones & Langley, 2005).

⁴ In computer science, production systems are forms of artificial intelligence (i.e., programs) consisting of a set of production rules that specify the behavior of the system. To create a new production rule is to create a new behavior necessary for dealing with a novel situation.

The power of models and methodologies, especially those borrowed from other fields, to shape scientific reality has been documented in many areas of science (Gigerenzer, 1991). Understanding the analogical process that led to the use of a model can help people recognize the worldview, assumptions, and methodologies that are transferred along with the model. Since analogies are used in uncertain situations when phenomena of interest are alien or obscure, the difference between models and reality may not be obvious. In addition, analogies are based on only partial similarities between domains, and applying analogical models focuses attention on some features of a complex reality while ignoring others. Confusing a model with reality increases the likelihood not only of imputing ill-fitting features of the model source to reality, but also of omitting important aspects of reality not captured by the analogical model. Recognizing the source of models used to represent target phenomena reminds people that they are dealing with models and not reality.

Analogies as themata

In our framework, analogies correspond to *thematic concepts*. Thematic concepts in turn provide grounds for methodological themata, which we simply call themata. For instance, reduction is a thema that emerged from classical mechanics. Themata are then defined in terms of conflicting *thematic positions*, such as reductionism and holism in the case of reduction. This simple duality can be more nuanced, and in the case of reduction we make a distinction between strong reductionism, weak reductionism, and holism. For simplicity our thematic map (Figure 2) merges weak reductionism and holism because they have methodological similarities, but we keep the distinction in the questionnaire study.

Gerald Holton applied thematic analysis to physics, his field of expertise. Since analogies from physics are pervasive in economics, his thematic framework is particularly

relevant for our study. Furthermore, our consideration of the psychological aspects of analogical reasoning augments Holton's approach. For instance, the recognition of analogies as cognitive tools for uncertainty connects thematic analysis with Kuhn's cycle of scientific revolutions. Specifically, our expectation that the use of analogies will increase in the parts of Kuhn's cycle where uncertainty is higher is based on our psychological approach.

Analogies for Economic Models

In this section we first present the historical context of the introduction of influential analogies into economics; second, we outline the methodological themata implied by those analogies; and finally, we construct a thematic map that provides means for answering our research questions.

We recognize two major families of analogies in economics: those from physics and those from the life sciences. We also consider an additional case: analogies from complexity science. Complexity science is a new scientific paradigm that represents a meeting point of physics and life sciences and perhaps an emerging trend in economics (Holt, Rosser, & Colander, 2011). We devote a separate subsection to the historical details of the evolution of mathematical models in economics. The relevant historical context includes mostly events that took place within physics but also the probabilistic revolution, which represents a special case of a scientific revolution inspired, in part, by analogies from the social sciences. Because physics played a role in the introduction of mathematical modeling in economics, that subsection is presented after analogies from physics.

Analogies from physics

Systematic considerations of human economic activities preceded Adam Smith by centuries, but at that time the issue was regarded as a part of ethics.⁵ Bringing his affection for mechanistic philosophy to the subject, Smith divorced economic concerns from moral philosophy and set the stage for their future quantitative treatment. The discontinuity was so radical that it was recognized as the emergence of a new discipline. A shared belief in economic laws⁶ as natural laws among classical economists suggests that the change was part of a more general process, the Enlightenment revolution.

Further progress of the new discipline can be attributed primarily to the development of two interrelated concepts: marginalism and general equilibrium. Jevons and Carl Menger are widely recognized as progenitors of the marginal revolution in economics. Inspired by the “field” theories of Michael Faraday and James Clark Maxwell, Jevons undertook the first steps to formalize Jeremy Bentham’s concept of utility,⁷ foundational for the future theory of consumer choice and operationalization of the equilibrium idea (Beinhocker, 2006; Mirowski, 1989).

A fundamental contribution, in terms of general equilibrium theory, came from the Lausanne School of economics, also known as the Mathematical School (Walras, 1874/1954). Two central figures of the school, Walras and Pareto,⁸ were both engineers.

⁵ For instance, human economic activities became a topic of systematic analysis in the work of Scholastic philosophers such as Thomas Aquinas or Albert the Great. In general, economic considerations that predate A. Smith’s *An Inquiry Into the Nature and Causes of the Wealth of Nations*, which announced the beginning of modern economics, are widely recognized as the era of Scholastic economics.

⁶ A prominent example is Say’s law, an economic principle formulated by the French classical economist Jean-Baptiste Say, which claims that total demand in an economy cannot exceed or fall below its total supply.

⁷ In one of his illustrative explanations of utility, Jevons stated that “utility is an attraction between a wanting being and what is wanted” and is “just” like “the gravitating force of a material body” (cited in Cohen, 1994, p. 43).

⁸ For more details on the mechanistic philosophy of Pareto’s work on economics, sociology, and political theory, see *Pareto, Economics and Society: The Mechanical Analogy*, by Michael McLure (2001).

Origins of Walras's revolutionary theory can be traced back to Louis Poinso⁹ considerations of the equilibrium tendencies of dynamic forces of moving bodies. In a paper from 1909, Walras argued that differential equations from his theory are identical to those employed in the explanation of behavior of two physical systems, namely, the equilibrium of a lever and the motion of planets based on celestial mechanics (Cohen, 1994). The problem of constrained optimization implemented in Walras's model was not new to Pareto,¹⁰ who introduced a new optimality concept and further improved the model. The influence of Walras's work, which Schumpeter (1954/1994, p. 827) compared with achievements in theoretical physics, was so far-reaching that his approach has become the main determinant of economic methodology ever since.

Irving Fisher and Paul Samuelson, seminal characters in modern neoclassical economics, were both trained physicists and strongly influenced by Willard Gibbs,¹¹ founder of the field of chemical thermodynamics. Trying to advance Walras's theory, Fisher was among the first to incorporate thermodynamics in the general equilibrium approach, but it was Samuelson who extensively explored the thermodynamic analogy. In his influential Ph.D. thesis, *Foundations of Economic Analysis* (Samuelson, 1947), which instantaneously after publication became a standard part of the modern economics curriculum, Samuelson applied a mathematical apparatus from classical thermodynamics to reshape almost all

⁹ Louis Poinso⁹ was a French physicist. William Jaffe, the leading authority on Walras's work, hypothesized that Walras's theory was strongly influenced by Poinso⁹'s popular-at-the-time textbook *Elements of Static* (first published in 1803), based on a letter in which Walras disclosed to a friend that he had first read the book at the age of 19 and had used it frequently throughout his life (Jaffe, 1965). Jaffe especially stressed the importance of the second chapter of Poinso⁹'s book, "On Condition of Equilibrium Expressed by Means of Equations" (Beinhocker, 2006).

¹⁰ Pareto described his first reaction to Walras's equations: "These equations do not seem new to me; I know them well, they are old friends. They are the equations of rational mechanics" (cited in Cohen, 1994, p. 41).

¹¹ One of the most important names in the revolution in physics and chemistry at the turn of the 19th and 20th centuries, Gibbs was Fisher's Ph.D. thesis mentor, but his influence on Samuelson was transferred through another of Gibbs's students, Edwin Bidwell Wilson.

aspects of economic theory¹² (Lo & Mueller, 2010). His assimilation of Keynesian macroeconomics into the neoclassical microeconomic framework was critical for the establishment of the neoclassical synthesis as a dominant theory of modern economics.

The import from physics into finance is particularly evident. Writing on the problem of option pricing in his Ph.D. thesis in 1900, French mathematician Louis Bachelier borrowed Joseph Fourier's probabilistic formula for the diffusion of heat through a substance to approximate the behavior of an option's underlying asset. A few decades later, this assumption became the main reference point of the optimal portfolio theory (Markowitz, 1952), the capital asset pricing model (Sharpe, 1964) and the option pricing theory (Black & Scholes, 1973; Merton, 1973), three major building blocks of modern financial theory (Mandelbrot & Hudson, 2010). A neoclassical account of financial market behavior in full accordance with Bachelier's assumption was provided by Eugene Fama and Samuelson in the efficient market hypothesis.

It was Benoit Mandelbrot (1963) who collected early empirical evidence that financial markets deviate from predictions of the mainstream theory based on the efficient market hypothesis. Growing criticism of linear stochastic explanations facilitated the introduction of nonlinear dynamic analysis, recently developed in physics and particularly in chaos theory, in economics. Tools of modern financial analysis, such as power laws, statistical mechanics, scaling arguments, random matrix theory, and ultrametric correlations, among others, confirm that nowadays financial markets belong to physicists as much as to economists (Farmer, Shubik, & Smith, 2005; Lo & Mueller, 2010). Mantegna and

¹² In his later writing on *Foundations of Economic Analysis*, Samuelson (1998, p. 1376) emphasized how he realized early on that economics and physics share the same formal mathematical theorems despite not resting on the same empirical foundation. In his interpretation, his economic models are nothing but mathematical isomorphism to those in thermodynamics (Samuelson, 1960).

Stanley (2000) announced the emergence of “econophysics,” and Farmer et al. (2005) described the recent institutional development of the new field.

We selected four concepts from physics responsible for shaping methodological positions in economics and finance. These are the mechanistic model, the thermodynamic model, the model of chaos, and the model of statistical mechanics. The first two found wide application in economics, and the second two, while not being that popular among economists, introduced significant novelties in economic modeling. To avoid repetition, after presenting the methodological presuppositions of the mechanistic model, we present only the novelties from subsequent models that changed a previously established methodological view. For this reason, for instance, we omit the evident role of classical electrodynamics, as its methodological influence falls under the mechanistic model.

Analogies from mechanics

Classical mechanics is based on the assumption that the world is governed by universal laws. In a so-called Newtonian or Laplace’s world, any state of the universe can be inferred from its initial conditions, given that we know the underlying physical laws. In simple words, if we have all the pieces of information, we “only” need to put them together to get the full picture. This approach was built while trying to understand “simple” physical phenomena, such as the behavior of falling objects or the interaction of moving objects but also the dynamics of celestial bodies.

The application of the mechanistic model to economic theory with examples of marginalism and general equilibrium theory was detailed above. The philosophy that physical phenomena can be explained by strictly following the cause-and-effect relationship

between events gave rise to several methodological presuppositions¹³: reductionism, closed system, reversibility, and equilibrium.

Reductionism. From the reductionist perspective, complex phenomena are just manifestations of universal laws that operate on the microscopic level. The reduction presupposition¹⁴ states that all features of a complex phenomenon can be explained by analyzing the interaction of an arbitrarily small number of its fundamental parts. Macro-level explanations are then obtained by the aggregation of analyzed interactions. We call this form of reductionism “strong reductionism.”

In physics, substances are disentangled to molecules and atoms, forces are broken down into vectors, fields into waves, waves into photons, and so forth. To arrive at the understanding of the behavior of many gas particles, for instance, it is sufficient if one explains the interaction of only two particles. An example is Boltzmann’s kinetic theory of gases. Similarly, orthodox economics decomposes complex social structures into individual consumers and firms. The economic reductionism goes even further by defining a representative agent,¹⁵ or a utility maximizer, whose actions can be “added up” in a simple way so that they actually represent aggregate choices in the economy (Kirman, 1992). Essentially, understanding the behavior of a single agent is assumed to be sufficient for building a macroeconomic model. The standard dynamic stochastic general equilibrium model, for instance, relies on the assumption of a representative agent (Colander, Howitt, Kirman, Leijonhufvud, & Mehrling, 2008).

¹³ More than three decades ago, John Moorhouse (1978) outlined mechanistic principles used in economic methodology, as well as their potential implications for economics.

¹⁴ In social science as well as in economics, the reduction principle is usually labeled methodological individualism, or its utilization as the microfoundation of analysis. The branch of economics based on methodological individualism is known as microeconomics.

¹⁵ “The idea that an individual behaves in accordance with certain typical patterns was essential for shaping economics as science” (Prokhorov, 2001, p. 6).

Closed system. Physical phenomena of the natural world are complex, and accounting for all the relevant factors that determine possible outcomes is beyond reach. To distill cause-and-effect relationships between factors of interest it is necessary to isolate them from the rest of the world. In practical terms, this means designing conditions in which exogenous factors cannot intervene and contaminate the observation. The applicability of isolation depends on the nature and complexity of phenomena. For instance, falling of a physical object can be relatively easily isolated, while weather phenomena cannot. Therefore, isolation is in a close relationship with the scope of scientific observation.

Classical mechanics is by and large a science of closed systems. To study the paths of, say, falling objects, their collisions, or gas particle interactions without unwelcome disturbances, classical physicists constructed isolated chambers, containers, gas balloons, and so forth. The observation was also confined to a small number of interacting factors. On the other hand, isolation in economics was mostly hypothetical because it could not be externally enforced. For instance, *ceteris paribus*,¹⁶ a widely used assumption in economics, is based on the premise that all factors that are not part of an observation stay constant. Similarly, the scope of observation was relatively limited. An example is a model of partial equilibrium that considers a single good market while assuming that there are no interactions with other markets. However, the mechanistic analogy also inspired an analysis that includes multiple markets, namely, general equilibrium analysis.

Reversible processes. Any process captured by mechanical laws can be reversed back to its initial state by the same laws that govern that process. In formal terms, dynamic equations that stand for the process are invariant to a change in the sign of time. This quality of mechanistic processes is known as reversibility. An illustration of a reversible

¹⁶ A Latin phrase for “all other things being equal.”

process is the swing of a frictionless pendulum. Reversible processes are not exclusively related to any specific point in time, as they can be returned to their initial state and performed again. This is why it is appropriate to say that mechanical processes are ahistorical.

In classical physics, any formal mechanistic model implicitly assumes reversibility. The kinetic theory of gases was relatively successful at predicting gas behavior because, in reality, relativistic and quantum-mechanical effects in many gases are negligible and their processes are hence almost reversible. The same applies to Walras's general equilibrium theory, which is a mechanistic model. Therefore, equilibrium processes of market price formations are assumed to be at least approximately reversible in this model.¹⁷

Equilibrium. When moved from the steady state, mechanistic processes tend to regain stability. In other words, if a force is applied to a mechanistic system, disturbing its balance, interacting forces tend to balance again. The formal expression of such an interaction, in which the corresponding vectors finally result in the outcome vector, is known as equilibrium calculus.

An example from physics is the mechanical lever, whose simple mechanism is about balancing between two opposing forces. The concept of the mechanical lever has been an important analogical model for the development of marginalism and general equilibrium theory.¹⁸ Equilibrium is the most widely adopted principle in economics and the trademark of economic analysis. On the micro level, it is intimately related to maximizing the behavior

¹⁷ Although the implications of reversibility in economics are not straightforward, there is ample empirical evidence that contradicts the reality of this assumption. The phenomenon of increasing returns inherent in various economic activities is an example of the path dependence of economic processes (Arthur, 1989). Since the nature of the issue is very technical we do not pursue the principle in the second part of the study.

¹⁸ In his seminal contribution, *The Theory of Political Economy*, published in 1871, Jevons formally described the lever mechanism (with a drawing), explaining in much detail the direct analogical parallels between the lever and his theory of exchange (Jevons, 1871/1888). It is worth saying again that Walras used the same analogy for his description of general equilibrium theory (Walras, 1909).

of market agents, and on the macro level to the formation of the overall market price. The former is related to marginalism and the latter to general equilibrium theory.

Analogies from thermodynamics

Thermodynamics is the study of relationships between the macroscopic state variables (e.g., pressure, temperature, energy, etc.) of a physical system when it is subject to change. In contrast to the mechanistic model, the focus is shifted from a difficult-to-observe micro level to a macro level that is easy to observe and measure. This led to observation of macro-level regularities known as the laws of thermodynamics. The established laws are essentially macroscopic-level constraints, which provide a valuable reference point for potential microscopic explanations.

Interpretations of the thermodynamic analogy in economics vary, because of the flexibility of its framework. Here, we pay special attention to Samuelson's application of equilibrium thermodynamics to market allocation problems,¹⁹ which had major implications for mainstream economic theory. There are at least two additional research programs in economics that stem from thermodynamics. One studies the use of materials and energy in consumption and production, and another studies macro sustainability of global economic systems (Ruth, 1996). Development of a novel perception of the economic system as an open system, assuming irreversibility, nonlinear dynamics, and nonequilibrium processes, has been significantly supported by insights from modern thermodynamics (Daly, 1968; Georgescu-Roegen, 1966). Besides statistical mechanics, this is another example in which modern physics played a role, albeit relatively limited, in mainstream economic theory.

¹⁹ The main reference point here will be the analysis of Samuelson's model by Eric Smith and Duncan Foley (2008).

Samuelson's thermodynamic analogy did not introduce novel themata but mostly reinterpreted thematic positions established in the mechanistic model. Although thermodynamics is not reductionist per se, the analogy was applied so that an individual economic agent was represented as a macroscopic system characterized by analogous macroscopic state variables. This interpretation of "economic particles" preserved their deterministic treatment and maintained the reductionist character of the model. Furthermore, the interactions between economic agents were limited to trade, which is an example of the closed system of isolation. Then the laws of thermodynamics were applied to the trade interactions modeled as the utility exchange, which eventually led to the equilibrium price formation. Therefore, equilibrium was preserved as a central concept in describing market behavior. Only reversibility was refuted, which was a matter of interpretation rather than a consequence that follows inevitably from thermodynamic equilibrium²⁰ (E. Smith & Foley, 2008).

Analogies from chaos theory

Classical chaos theory is the study of behavior of nonlinear deterministic systems, which can be observed in a variety of real-world phenomena. This can be understood as an attempt of physics to get involved in the more "complicated" aspects of physical reality, later labeled complex systems. Dynamic chaos models are characterized by intrinsically generated stochasticity and high sensitivity to initial conditions and parameter values (Prokhorov, 2001). The former means that these models exhibit irregular behavior, which practically is hard to distinguish from pure random patterns. The latter means that even a very small difference in initial conditions can have a huge impact on the outcomes. On a

²⁰ In fact, Smith and Foley (2008) argued that irreversible transformations are generally not predictable in equilibrium theories and suggested that considering reversible transformation is more consistent with the equilibrium framework.

conceptual level, chaos theory studies mathematical properties of deterministic nonlinear models and tries to explore how they relate to observed features of complex systems. The realm of complex systems includes the majority of natural systems such as organisms, ecosystems, and climate, and various products of human activity such as urban areas, social networks, or financial markets. For instance, the observation of weather phenomena played an important role in understanding the context of a large number of interacting factors and their nonlinear interdependencies.

An early prototype model in nonlinear economic analysis was a nonlinear business cycle model introduced by Kaldor (1940; Lorenz, 1993). With new assumptions, nonlinear macroeconomic models were able to simulate endogenously generated erratic behavior, which previously was typically modeled by means of external random shocks. Such models were more apt to explain tipping points, fractal patterns, and long-term memories, properties that financial markets regularly exhibit.

Chaos theory as a study of system dynamics is not directly concerned with microscopic processes of the system. However, the insights from the observation of chaotic systems carry important implications for reductionist theories. An intrinsic sensitivity to initial conditions of chaotic systems together with small initial errors, inevitable given that initial conditions can only be approximated, generates huge mistakes in outcome predictions.²¹ In the model of chaos, isolation is applied on an entirely different level because the focus is shifted from observation of a few objects or forces to observation of

²¹ This conclusion can be traced back to Henri Poincaré, who summarized it in 1903: “Even if it were the case that the natural laws had no longer any secrets for us, we could still only know the initial situation approximately. If that enabled us to predict the succeeding situation with the same approximation, that is all we require, and we should say that the phenomenon had been predicted, that it is governed by [deterministic] laws. But it is not always so; it may happen that small differences in the initial conditions produce very great ones in the final phenomenon. A small error in the former will produce an enormous error in the latter. Prediction becomes impossible, and we have the fortuitous phenomenon” (cited in Prokhorov, 2001, pp. 9–10).

large systems with numerous interacting factors, such as ecosystems. Furthermore, chaotic processes are irreversible and path dependent. This implies that time matters and that the chronology of events determines historical outcomes. An illustrative example is a market phenomenon known as increasing returns (Arthur, 1989). Finally, chaos theory is concerned with processes that are rather far from equilibrium and searches for patterns in apparently irregular behavior of dynamic systems. This is supported by the observation that almost no processes in nature are in steady states, and even among those that are, equilibrium states are only their special cases. Moreover, there are strong indications that complex systems require far-from-equilibrium conditions to maintain self-organization or growth (Prigogine & Stengers, 1984).

Analogies from statistical mechanics

Statistical mechanics applies probability theory to study behavior of mechanical systems. Instead of tracing the dynamics of individual microscopic particles of the system, statistical mechanics deals with their average behavior. The novelty of the probabilistic approach led to establishing the missing connection between microscopic processes and macroscopic quantities, observed and measured in classical thermodynamics. Calculation of pressure in a gas system based on statistical mechanics, for instance, disregards the record of any particular gas particle and calculates on average how many particles per time unit hit the wall of the gas chamber.

Unlike in the cases of mechanistic and thermodynamic analogies, methods of statistical mechanics were not introduced to the field by economists, but by physicists themselves (Jovanovic & Schinckus, 2013). Examples of applications are the use of multifractal models in econometrics, or scaling laws in modeling income, wealth, or firm distributions. On the theoretical level, the probabilistic perspective opened new doors for

dealing with the aggregation problem, which previously led to the development of highly unrealistic single-actor macroeconomic models. The main benefit is that modeling of collective actions does not require sacrifice of agents' interactions because of the limitations of the theoretical framework (Lux, 2008).

Since the focus is not on individual behavior of microscopic particles but on statistical properties of their collective actions, a different sort of reductionism is assumed, which we refer to as weak reductionism. The interest in collective behavior and applications of statistical mechanics in modeling interactions in complex social phenomena (Galam, 1986; Weidlich, 1971) implies that isolation is practically shifted to the level of complex systems. Statistical mechanics is also applied outside equilibrium, in which modeling irreversible processes plays a major role.

Evolution of mathematical models in economics

French mathematician Antoine Augustin Cournot is widely considered a pioneer of mathematical economics. In the first half of the 19th century he introduced the notion of function in economic analysis, deriving the law of supply and demand as a function of price. Mathematics was the main instrument in the work of Jevons, Edgeworth, Walras, and Pareto. Their legacy in terms of marginal revolution and general equilibrium theory has made the mathematization of economics irreversible. John Hicks, a British economist and mathematician, made important improvements to Walras's model and introduced Walras's work to the English-speaking world. Since the Walrasian model left ample room for mathematical improvement, it was further advanced by mathematicians²² in the mid-20th

²² Mathematicians played one of the critical roles in economics of the 20th century. For instance, the two most influential macroeconomists of that time, John Maynard Keynes and Milton Friedman, were both trained mathematicians. Just as

century. With the contributions of Kenneth Arrow, Gerard Debreu, and John Nash, the model reached full axiomatization.

Despite being a social science, economics started using mathematical formalism as its main language not long after Adam Smith. Mathematics entered economics via physics, and their influences on economics are closely related. Three turning points in the history of natural sciences have significantly changed formal modeling in economics: The first was the spreading of a natural philosophy of universal laws that encouraged economists to adopt mathematical models from classical physics; the second was when the probabilistic revolution transformed a deterministic worldview into a stochastic one; and the third was when a worldview with normally distributed phenomena and linear models was confronted with a worldview of power laws and nonlinearities. In what follows we describe four influential mathematical worldviews used in economics.

Linear deterministic model

Linear models are based on the assumption that the interactions of different isolated phenomena occur in an additive manner. The principle of superposition,²³ which directly reflects the Newtonian linear paradigm, implies that “the most general motion of a complicated system of particles is nothing more than a linear superposition of the motions of the constituent elements” (West, 1985, cited in Lorenz, 1993, p. 13). In this worldview, the initial conditions and set of linear equations capturing the observed processes allow for deterministic predictions. Since classical physics was the exemplar model of the time, it is no

Fisher and Samuelson promoted mathematics before them, scholars of the highly influential Chicago school of economics championed a strong mathematical culture. Some of the most important scholars of the Chicago school were Frank Knight, Georg Stigler, Milton Friedman, Gary Backer, Robert Lucas, and Eugene Fama.

²³ Superposition is a mathematical characteristic of linear models that is defined as follows: If two inputs x_a and x_b have outputs y_a and y_b , respectively, then in a linear model the input $x_a + x_b$ will give the output $y_a + y_b$.

surprise that early economics was linear²⁴ (Lorenz, 1993). While deterministic models are more rare, linear models are still commonplace in modern economics. The Smets–Wouters dynamic stochastic general equilibrium model, which the European Central Bank used prior to the crisis, is an example of a linear model.

Linear stochastic model

Events that led to the probabilistic revolution involved observation of social rather than natural phenomena. This is a quite rare example in the history of science of the natural sciences learning from the social sciences. Even though some forms of risk assessment were used in the ancient civilizations of China, Babylon, Greece, and Rome (Nozer & Wilson, 2008), the first use of probability calculus is commonly associated with the discourse between Blaise Pascal and Pierre Fermat on problems relating to games of chance. At around the same time, insurance companies started using simple statistical methods to assess the likelihood of shipwrecks, fires, or similar accidents against which their customers wanted protection. The first known application of the probability calculus in physics occurred when Pierre Simon, marquis de Laplace, the French mathematician, took advantage of probabilistic techniques to circumvent the problem of measurement errors made by astronomical instruments. Laplace realized that errors in telescopic observations formed a particular pattern. Not long afterward, Adrien-Marie Legendre and Carl Friedrich Gauss provided a mathematical formalization of the normal distribution. The next advance, however, took place in the backyard of social science, when Adolphe Quetelet²⁵

²⁴ A linear worldview can be observed, for example, in the writing of classical economist John Stuart Mill in 1844: “There are not a law and an exception to that law—the law acting in ninety-nine cases, and the exception in one. There are two laws, each possibly acting in the whole hundred cases, and bringing about a common effect by their conjunct operation” (cited in Prokhorov, 2001, p. 7).

²⁵ Quetelet, an astronomer and a student of Laplace, introduced the term “social physics,” giving a clear hint about the origins of the analogy for his theorizing about social phenomena. He recognized normality in records of births, marriages,

demonstrated the power of statistical techniques to deal with large demographic databases in order to make population-level predictions. Quetelet's contribution was evidently a key inspiration for Boltzmann and Maxwell to use statistical tools and independently derive gas theories on a completely novel basis (Gigerenzer et al., 1989, p. 45). Their work soon inspired revision of classical physics and led to the development of statistical physics.

The probability revolution had a particularly important role in financial and macroeconomic models that were naturally focused on capturing the dynamics of the economy. Probability was introduced in finance by Bachelier at the very beginning of the 20th century. However, that was one man's intuition rather than a product of economic thought of the time.²⁶ Accumulation of financial time series posed a serious challenge in terms of understanding the mathematical properties of functions describing observed fluctuations of macroeconomic and financial fundamentals. In addition to linearity, Bachelier's type²⁷ of stochasticity strongly characterized economic modeling in the first half of the 20th century. Since that time, the normality assumption has been used to model fluctuations in all kinds of physical and social phenomena.

In finance, the normality assumption suggests that movements of market prices form the bell curve. Known also as Gaussian, the normal distribution belongs to a class of parametric distributions with a very convenient mathematical property, namely, that it can

deaths, suicides, crimes, etc. He is also known for his idealistic concept of the average man that supposedly can be used as a standardized agent for modeling social phenomena. It is also worth mentioning that credit for the discovery of "social laws" by means of probabilistic interpretation is typically shared between Quetelet and Henry Thomas Buckle (Gigerenzer et al., 1989).

²⁶ A few decades later an awareness of the discrepancy between economic modeling and economic reality started to develop. In his presidential address to the American Economic Association in 1924, Wesley Mitchell said, "The statistical view involves the notions of variety, of probability, of approximation.... The mechanical type of speculation works with the notions of sameness, of certainty, of invariant laws. In economics these notions do not fit the phenomena closely. Hence we must put our trust in observations" (cited in Prokhorov, 2001, p. 8).

²⁷ Bachelier's original model of price movements has been revised by many authors (Kendall & Hill, 1953) who assumed that return rates but not stock prices follow Brownian motion. Thus, in modified models the oscillations of stock prices form a log-normal distribution rather than the normal distribution proposed by Bachelier.

be characterized by only two parameters, mean and variance. The latter has become the ultimate measure of risk in modern finance.

Nonlinear deterministic model

The mathematical concept of chaos brought one of the last significant changes to economic modeling in the 20th century. About four decades after Poincaré showed that seemingly stochastic behavior can be generated from a deterministic process, Kaldor (1940) introduced nonlinearities in a business cycle model. Popularization of nonlinear modeling in economics can be largely attributed to Mandelbrot (Mirowski, 1990). The result was that assumptions of linearity, independence, stationarity, and normal distributions were challenged with nonlinearity, time dependence, nonstationarity, and power laws (Mandelbrot & Hudson, 2010). Some pioneers of chaos in economics were William Brock, Blake LeBaron, Richard Day, and James Ramsey (Prokhorov, 2001). The uncovering of long-term memories in financial data is an illustration of how the concept of chaos gradually advanced the understanding of financial markets, debunking some deeply entrenched assumptions of the neoclassical model (Lillo, Mike, & Farmer, 2005).

Nonlinear stochastic model

Achieving a clear distinction between high-order chaos and an infinite dimensional (stochastic) process is still a work in progress, as well as determining which of the two is a better descriptor of macroeconomic dynamics (Brock & Malliaris, 1989). The most representative of nonlinear stochastic models is the ARCH (autoregressive conditional heteroskedasticity) model proposed by Robert Engel in 1982. Generalized by Tim Bollerslev (GARCH), the model encouraged a large amount of subsequent research that resulted in a whole class of ARCH models (Bollerslev, 2010). The most distinctive innovation introduced by ARCH is the treatment of time dependencies in higher order moments (such as variance

and covariance). This so-called conditional treatment of variables, in which their current values depend on the past states of the world, was motivated by clustered volatility observed in the financial markets (Bollerslev, Chou, & Kroner, 1992).

Analogies from the life sciences

Alfred Marshall's (1890/1920, p.19) well-known statement, "The Mecca of the economist lies in economic biology rather than in economic dynamics," is widely considered an early indication that biology can be a valuable source of inspiration for economics²⁸ (Daly, 1968; Hodgson, 1997). Another early hint came from the leading institutionalist Thorstein Veblen, who in 1898 entitled a paper "Why Is Economics Not an Evolutionary Science?" and coined the term evolutionary economics. The leader of alternative economic thought at the time, Veblen criticized the neoclassical paradigm by pointing out that uncertainty, complexity, and emergence are inherent properties of economic reality. There are at least four distinctive evolutionary approaches in economics (Witt, 2008). First, probably the most prominent evolutionary economist, Joseph Schumpeter (1912/1934), held that the concept of natural evolution is inappropriate to deal with the fast progress of capitalist societies. In his at-the-time radical theory of business cycles, Schumpeter identified technological innovation as the primary source of "creative destruction." In the Schumpeterian framework, entrepreneurs are the main generators of change and discontinuity in an otherwise self-balancing economic reality. Second, while acknowledging

²⁸ Even though he never formally developed the biological analogy (Thomas, 1991), Marshall insisted on including this statement in all subsequent editions of his classic textbook, *Principles of Economics*. Marshall (1890/1920, p. 19) justified his inconsistency as follows: "The Mecca of the economist lies in economic biology rather than in economic dynamics. But biological conceptions are more complex than those of mechanics; a volume on Foundations must therefore give a relatively large place to mechanical analogies; and frequent use is made of the term 'equilibrium,' which suggests something of statical analogy." Moreover, in the later appendixes of the book he characterized economics as a branch of biology (Thoben, 1982).

certain specifics of social and economic evolution, Veblen (1898), Georgescu-Roegen (1971), and Hayek (1971) were strongly inspired by the ideas of natural evolution. Some of their important evolutionary concerns were innovation and human creativity; processes of novelty dissemination, such as imitation and learning; and sustainable growth and long-term development. Third, in their seminal book, *An Evolutionary Theory of Economic Change*, Nelson and Winter (1982) developed a comprehensive evolutionary framework, adopting abstract principles of natural selection without strictly sticking to Darwinian ontology.²⁹ The model was the first highly formalized framework designed to address the question of how novelty, innovation, and change are endogenously generated in the economic system. Finally, Hodgson and Knudsen's approach (Hodgson & Knudsen, 2006), labeled by Witt (2008) as "universal Darwinism," embraced the Darwinian worldview and natural selection as the most promising explanatory framework for addressing evolution in both natural and social domains of reality.

Another independent branch of economic research found inspiration in ecology. Ecology is often referred to as the economy of nature (Costanza, 1996). Both economics and ecology study the allocation of scarce resources, one in humans and the other in the rest of the living world.³⁰ Stressing strong connections between the fields, some authors began to protest against this artificial separation of two segments of reality and their mutual disregard (Daly, 1968). Moreover, attempts to bridge the gap arose on both sides. Since the beginnings of ecology as a science there has been a tendency to account for the human

²⁹ They described their pragmatic attitude as follows: "We emphatically disavow any intention to pursue biological analogies for their own sake, or even for the sake of progress toward an abstract, higher-level evolutionary theory that would incorporate a range of existing theories. We are pleased to exploit any idea from biology that seems helpful in the understanding of economic problems, but we are equally prepared to pass over anything that seems awkward, or to modify accepted biological theories radically in the interest of getting better economic theory" (Nelson & Winter, 1982, p. 11).

³⁰ These were originally common points of view in both fields. Unlike modern ecology, mainstream economics is still very close to its initial position.

factor. H. T. Odum (1971), Meadows, Meadows, Randers, and Behrens (1972), and Holling (1973) were early proponents of the holistic ecological view (Costanza, 1996). Influenced by Georgescu-Roegen, Kenneth Boulding (1966) and Herman Daly (1968) popularized the use of the concept of entropy when studying the relationship between the economic system and the environment. This inspired the establishment of environmental economics, a branch of the mainstream approach that employs standard economic analysis to study the ecological costs of human economic activity. Externalities, market failures, overharvesting of resources, and environmental degradation have been addressed primarily for the sake of sustainable economic development. However, in the 1980s, one group took a more radical position (Daly, Richard Norgaard, and Matthias Ruth, among others) and together with like-minded ecologists (Robert Costanza, Charles Hall, Ann-Mari Jansson, H. T. Odum, David Pimentel, and others) organized a series of seminars on the integration of ecology and economics. The joint effort culminated in 1988 when the International Society of Ecological Economics was founded, and a year later the journal *Ecological Economics* published its first issue. The leading authors persisted in presenting transdisciplinarity and interdisciplinarity as deliberate and essential qualities of the new field (Costanza, 1996). Accordingly, we recognize two major concepts from the life sciences that found use in economics: evolutionary theory and ecology.

Analogies from evolutionary theory

Change occupies a central position in any evolutionary approach. Consequently, the main interest is placed on studying processes rather than states. In particular, evolutionary biology studies adaptive changes in the heritable features of biological populations acquired under environmental pressure over generations. Evolution is a very broad concept relevant to a variety of phenomena, yet there are certain innate properties of evolutionary ideas that

hold across its various applications. In fact, many of those properties have been explicitly discussed within evolutionary economics (Fagerberg, 2002; Hodgson, 1998).

Discontinuity. In addition to incremental dynamics, mostly characterized by slow and quantitative change, evolutionary theory emphasizes discontinuous dynamics described by sudden and qualitative change. The study of discontinuities therefore deals with disturbing factors of the system's stability, and far-from-equilibrium concepts are of particular relevance. The ultimate form of discontinuity in evolution is the emergence of novel structures or functions. Emergence is a systemic process through which properties and or structures come into being that are unexpected, given the known attributes of component agents and environmental forces³¹ (Lichtenstein & McKelvey, 2011). Emergent features are understood as an organism's responses to adaptive pressure that require constant struggle with an ever-changing environment. Organisms with acquired adaptive features are more likely to survive, further disseminating those features in the population.

Even though, or maybe because, much of natural evolution can be associated with incremental change, evolutionary biologists are particularly interested in emergent properties of organisms. For instance, the question of how the cell evolved to be an independent functional entity, or even more fundamentally, how life emerged from nonorganic matter, are deep concerns of evolutionary biology. Similarly, evolutionists in economics are interested in the change of structural and organizational properties of the economic system, more than in pure augmentation of old structures. The emergence of companies and institutions, as well as new organizational structures, is a corresponding

³¹ Emergence is a complex and controversial concept, but at the same time it is widely considered to be the central property of complex systems. For more detail, see Lichtenstein and McKelvey (2011).

example of interest in evolutionary economics. Emergence and dissemination of novelty are generally identified as generators of economic development³² (Witt, 1996).

In evolutionary economics, it is common to make a distinction between approaches that model innovation endogenously and exogenously. For instance, in Nelson and Winter's model the innovation process is placed within the system. They also demonstrate that the heterogeneity of existing structures and its continuous restoration are critical requirements for the system's ability to generate innovations (Fagerberg, 2002). In contrast, the Schumpeterian model perceives creative individuals (i.e., entrepreneurs) as the main source of novelty that brings innovations to the system from the outside.³³

Complex systems. The evolutionary process takes place in a complex environment characterized by uncertainty, nonlinearity, and irreversible processes. Complexity in this context results from the involvement of numerous interacting elements that produce emergent phenomena and self-organizational patterns. Nonlinear relationships that are typical of such settings are associated with conditions of high uncertainty, which implies very limited predictability.

Complex social structures are pervasive in biology and economics. The cohabitation of a great variety of species, their competition for life space and reproduction, as well as the struggle for survival in food chains are just a few layers of the complexity in biological systems. Similarly, economic systems rest on a large number of interacting agents and exhibit various features of complex systems. Bubbles, crashes, herd behavior, and high

³² Fascination with the progress of capitalism has always been a strong motivation for the evolutionary study of economic systems. Consequently, attention in evolutionary economics is directed toward progress and constructive rather than destructive processes. However, in ecological economics, this interest shifts in a different direction that will be discussed in the next section.

³³ It is worth saying that the described difference can be largely attributed to the fact that Nelson and Winter's model suffers many practical constraints because of its higher level of formalism. For instance, to include the above-mentioned Schumpeterian concerns one needs to formalize the role of creative individuals and science in an economic system.

unpredictability of financial markets are common examples. Distinctive human features such as foresight and intentionality, communication, and technology seem to further ramify human complex systems (Holling, 2001). In trying to account for the complexity of the economy, evolutionary models are often analytically intractable, and solutions are instead explored through simulations (Fagerberg, 2002).

Bounded rationality. Given the uncertainty of the environment and the limited time, resources, and cognitive abilities of agents, rational models of “economic man” are highly unrealistic (Gigerenzer & Selten, 2001; Simon, 1947). Instead, the concept of bounded rationality assumes that agents who have evolved in such real-world conditions are equipped with adaptive behavioral rules, or heuristics (Gigerenzer, 2011; Simon, 1955). Heuristics are agents’ adaptive responses to the uncertainty of the environment, rather than products of an omniscient behavioral mechanism that provides the optimal response to any situation (Todd, Gigerenzer, & the ABC Research Group, 2012).

In the face of inherent constraints imposed by reality, models that assume maximizing behavior are pervasive in biology (Hutchinson & Gigerenzer, 2005) and dominant in economics (Nelson & Winter, 1982). However, justifications are typically different. In biology, optimization is not embedded in unbounded agents, but the evolutionary process itself is the optimization agent that selects an adaptively superior behavior (Alchian, 1950; Hammerstein, 2001). In economics, the maximizing behavior is, in contrast, a product of the as-if models of the human rational mind. In the former case, optimization is an attribute of the process and in the latter it is an attribute of the agent. However, the importance of bounded rationality is well understood in evolutionary economics. For instance, Nelson and Winter’s interpretation of bounded rationality

combines Simon's (1955) satisficing behavior and ideas from Cyert and March's (1963) behavioral theory of the firm.

Analogies from ecology

Ecology is an interdisciplinary science that studies interactions between organisms and their environment. The environment includes living and nonliving aspects of the organisms' habitat, such as other organisms, geography, or climate. Importantly, they are all changing and coevolving together. Therefore, by definition ecology deals with a blend of complex systems and their interrelationships. One of the deep concerns of ecology is sustainability, which can be simply defined as the capacity to endure (Bromley, 2008). In this context, ecologists develop methodologies based on holism, open system analysis, complex systems, and resilience.

Holism. Holism is the idea that properties of complex phenomena cannot be fully understood by analyzing only a small number of its fundamental parts. Interactions of numerous and often heterogeneous components of complex systems lead to the emergence of properties that cannot be scaled up from the observation of a few micro-level interactions. Therefore, the holistic approach entails investigating links among general (e.g., structural or functional) properties of the system or analyzing the interactions of a large number of system components (agents) in the form of computational models (in our questionnaire study we refer to the computational models as a "weak reductionism").

A typical analysis in ecology is to look for spatial and temporal patterns of driving variables (e.g., biodiversity, climate factors, etc.) that are assumed to be related to a targeted system property, for example, resilience (Walker, Holling, Carpenter, & Kinzig, 2004). The network approach (Janssen et al., 2006), comparative study of different complex systems (Costanza, Kemp, et al., 1993), and agent-based models (Grimm et al., 2006) are

typical tools for investigating problems within this framework. Likewise, ecological economics harbors a strong holistic view (Costanza, Wainger, Folke, & Mäler, 1993) and uses similar methodological techniques for studying socioecological systems (van den Bergh & Verbruggen, 1999).

Open system. The socioecological system is a concept that integrates economic, ecological, and social systems (Holling, 2001). None of the systems is observed strictly in isolation; rather, their interaction is the central issue. On the other hand, in mainstream economics the economy is by and large treated as a closed system. Interactions with the environment or other spheres of human social activity are rarely part of its focus. Consequently, in the orthodox methodology, factors that are from the ecological view naturally part of a particular analysis are regularly left out. For instance, in his growth model of a sustainable economy, Solow (1956) assumed an exogenously determined set of preferences and property rights, invariant to the state of the system. In contrast, the position of ecological economists is that a model with such assumptions is ignorant of feedback loops that are generated in dynamic interactions between human and environmental systems (Common & Perrings, 1992).

Complex systems. Discontinuities, emergence, nonlinearities, and self-organization are inherent to ecosystem dynamics, and they are all descriptors of complex systems (C. R. Allen & Holling, 2008). In addition to biological complexity, discussed above, there is evidence that human activity tends to introduce further complexities into already complex natural environments (Liu et al., 2007). In fact, the socioeconomic system integrates a large number of natural and social complex systems, and ecological economics recognizes links between human and ecological subsystems as being particularly important (Berkes & Folke, 1998). Such systems operate far from equilibrium, and concepts of discontinuity, transition,

regime shift, tipping points, and instability are essential for understanding their behavior (C. R. Allen & Holling, 2008; Scheffer et al., 2012). Unlike evolutionary economics, which deals primarily with discontinuities linked to system progress, such as innovations, ecological economics is concerned with discontinuities that affect system structures and functions that are caused by environmental disturbances. Critical transitions and catastrophic shifts are examples of this sort of discontinuity (Scheffer et al., 2009).

Resilience. Resilience is a quality that measures the system's ability to persist. The ecological literature recognizes two types of resilience: engineering and ecological (Grimm & Calabrese, 2011). Engineering resilience is defined as the rate and speed of return to preexisting conditions after disturbance (Holling & Gunderson, 2002). Ecological resilience in Holling's (1973, p. 14) structural view "determines the persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist." In addition to preservation of structural properties of the system, more recently the Resilience Alliance added a functional component to the definition: "Resilience is the capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks" (Walker et al., 2004, p. 5). The difference in the definition of engineering and ecological resilience reflects contrasting worldviews. Engineering resilience is a stability concept useful for near-equilibrium systems and essentially focuses on a single, global equilibrium state (Gunderson, 2000). In such a model the major concern is to support a system's return to equilibrium after a disturbance, which is usually exogenous. In contrast, ecological resilience is designed for the far-from-equilibrium behavior of ecological systems. Multiple equilibria, or rather domains of attractions (also called regimes), are acknowledged and even simultaneously considered

(Gunderson, 2000). Such an analysis highlights the importance of transitions from one regime to another and tipping points as critical events on the transition path (Scheffer et al., 2009, 2012).

Analogies from complexity science

The idea that reductionism as a universal analytical approach has serious limitations came from physics. Insights by Maxwell, Boltzmann, and Poincaré ushered in chaos theory. From the second half of the 19th century, the foundations of the complex system paradigm began to be noticed. Feedback loops (Maxwell, 1868), nonlinearity and sensitivity to initial conditions (Poincaré, 1887), self-organization (Ashby, 1947), and irreversible and far-from-equilibrium dynamics (Prigogine & Defay, 1954) were major insights leading to the new paradigm.

Alexander Bogdanov's approach (Gorelik, 1975) was an early precursor of the alternative holistic approach. In the 1910s Bogdanov outlined the principles of general system organization with the idea of unifying physical, biological, and social systems (Bogdanov, 1980). Since the Second World War, system analysis has become the main determinant of approaches dealing with complex systems (O'Neill, 2001). With roots in classical control theory, a branch of engineering research established cybernetics (Wiener, 1948) and system dynamics (Forrester, 1958). Similarly, research in biology gave rise to general system theory (von Bertalanffy, 1950). In 1954 Ludwig von Bertalanffy and others³⁴ founded the Society for the Advancement of General System Theory.³⁵ Thus, system

³⁴ Other well-known cofounders were Anatol Rapoport, Ralph Gerard, and Kenneth Boulding.

³⁵ In 1956 the society was renamed the Society for General System Research and in 1988 it became the International Society for the Systems Sciences.

thinking emerged in diverse disciplines such as biology (Miller, 1972), ecology (Holling, 1973; E. P. Odum, 1953), and psychology (Barker, 1968).

The idea of a multi-level structure of complexity,³⁶ introduced by Simon (1962), was one of the first direct links between system theory and complex systems (Lane, 2006). Since then, authors from various fields such as physics (P. W. Anderson, 1972), ecology (T. F. H. Allen & Starr, 1982), biology (Salthe, 1985), and computer science (Holland, 1992a) have recognized hierarchy as a key principle for understanding the organization of complex systems. An even more important message was that such systems, despite the complexity, share a relatively simplistic order regardless of their physical, biological, or social nature (Simon, 1962).

The collection of converging interdisciplinary insights led to the development of a more specific concept, a complex adaptive system (Holland, 1992b). This kind of complex system is described as an adaptive nonlinear network responsive to the environment so that it is capable of learning from experience, anticipating change, and adapting accordingly. The connections were obvious to some economists who immediately suggested that the model of complex adaptive systems is a better way to think about economic phenomena. As a result, the first conceptual and formal foundations of complexity economics were developed in the late 1980s at the Santa Fe Institute for Complex Systems.

Apart from the already discussed properties of complex systems, such as nonlinear interactions, far-from-equilibrium dynamics, and self-organization, the application of complexity approach carried two particular methodological implications for economics (Arthur, Durlauf, & Lane, 1997). First, instead of one universal behavioral model, namely,

³⁶ The concept assumes that subsystems of a system are hierarchically organized, such that each has subordinate subsystems eventually leading to elementary subsystems at the bottom of the hierarchy.

the rational actor model endorsed in the neoclassical economic theory, complexity economics allows that agents endowed with a limited cognitive capacity use a variety of cognitive processes while solving problems under uncertainty. Second, the structure of economic interactions is important and cannot be represented merely through impersonal market relationships, or one-to-one “game theory style” settings. Instead, network approaches are suggested as a tool that provides realism to modeling the structure of market interactions. Examples of the application across different domains are network models of social (Barabási et al., 2002; Brockmann & Helbing, 2013), biological (Albert, 2005), ecological (McCann, Hastings, & Huxel, 1998), engineering (Guimerà, Mossa, Turttschi, & Amaral, 2005), and financial (Arinaminpathy et al., 2012; Gai, Haldane, & Kapadia, 2011) systems.

A related approach to studying complexity has been agent-based modeling. An early example is Schelling’s (1971) model of emergent racial segregation in cities, where individuals using simple behavioral rules generate complex social dynamics. Both agent-based and individual-based simulations have been developed into well-established simulation techniques (Grimm et al., 2006). A pioneering work of this kind applied to finance was an artificial stock market model developed by researchers from the Santa Fe Institute (Palmer, Arthur, Holland, LeBaron, & Tayler, 1994). Founded in 1984, the Santa Fe Institute was the first to gather patches of complexity research from different domains in one place. John Holland’s (1992a) genetic algorithm, capable of accounting for agents’ adaptive behavior, and Langton’s “artificial life” model (Langton, 1986) based on cellular automata, had a strong impact on the modeling of complex economic systems (Rosser, 1999). Examples are Epstein and Axtell’s (1996) model of artificial societies with multiple markets and Albin and Foley’s (1998) model of the evolution of market structures. Large-scale

projects such as FOC (Forecasting Financial Crisis) and CRISIS (Complexity Research Initiative for Systemic Instabilities), which aim to understand and forecast systemic risk and global financial instabilities, illustrate recent trends in complex systems simulations (Farmer et al., 2012).

Thematic map

In what follows, we construct a thematic map to organize the themata presented above into congruent methodological worldviews (Figure 2). The complete list of themata that appear in the thematic map, sorted into 10 categories, is given in Table 1. The included themata are also heterogeneous: Some suggest relatively clear methodological instructions, such as reduction and isolation; others are more a consequence of the nature of observed phenomena and formal modeling applied, such as reversibility; and some more than others are a matter of economic interpretation, such as the rational actor model, which does not have a clear corresponding concept in classical physics.

As shown in Figure 2, we recognize two distinct analogical worldviews in economics: The classical physics worldview rooted in the mechanistic and thermodynamic models, and the life sciences worldview rooted in the evolutionary, ecological, and complexity models. We also find that the chaotic and statistical physics models do not easily fit into either of the two categories and alone do not represent a coherent methodological worldview. The methodological worldviews are not simple lists of thematic positions but rather can be understood as a set of closely interrelated ideas. For instance, reductionism suggests placing economic agents in the center of the analysis, whereas equilibrium suggests optimal allocations. Together they suggest the rational actor model, especially if strong reductionism is assumed, in which macro properties (optimality in this case) are supposed to be reflected

at the micro level. Holism, on the other hand, does not require a rational actor as it allows that macro properties can be emergent and independent from underlying micro properties. Similarly, a rational actor dwells in a certain environment, whereas an agent with bounded rationality fits better with an uncertain environment.

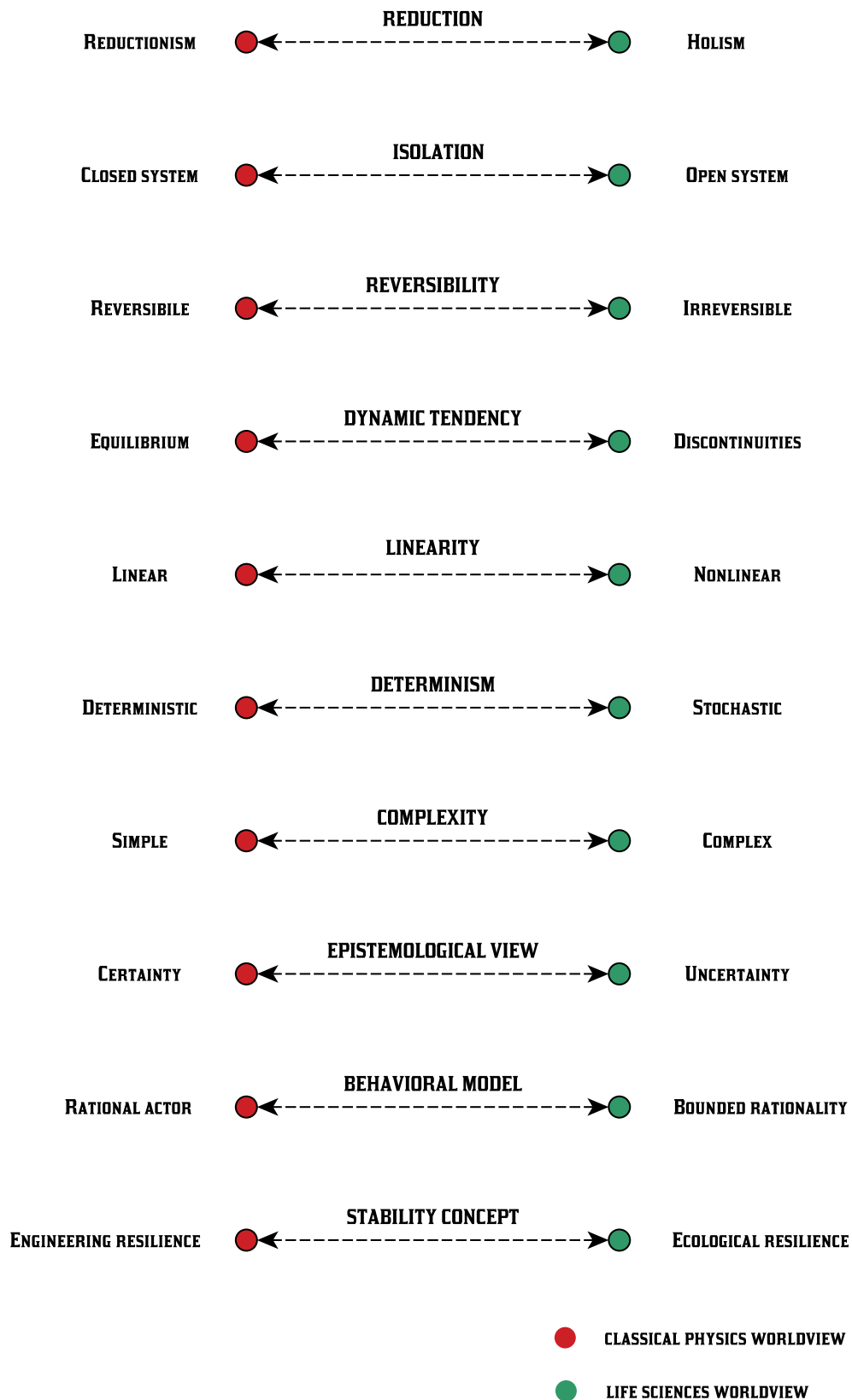


Figure 2. Analogical worldviews depicted in the thematic map. Themata are labeled with capital letters and placed above the dotted arrows. Thematic positions are placed at the opposite ends of the arrows.

This interconnectedness between the thematic positions explains why worldviews are resistant to change, as the replacement of a single thematic component can affect the remaining components. For instance, salvage of the rational actor model in the face of an uncertain economic world required the additional assumption that uncertainty can be reduced to risk. In a risky environment, in which probabilities associated with all possible outcomes are known, a rational actor capable of Bayesian updating can operate and make optimal decisions.

The thematic map also provides a tool for testing our research questions. In this context, the thematic map can be understood as a representation of methodological space defined by opposing thematic positions (such as strong reductionism and holism) located at the ends of the lines representing the themata (such as reduction, isolation, etc.). The methodological space of the thematic map is continuous. For instance, weak reductionism, even though it is very close to holism, belongs in between strong reductionism and holism. Similarly, risky environment belongs in between certain and uncertain environment. Since we aim to assess the methodology of the economics field, which naturally includes a variety of approaches, its average methodological position should be situated within the extreme poles of the methodological space. For instance, it is common knowledge that present-day economic modeling cannot be completely characterized as linear or deterministic. If the classical physics model is taken as a reference point, it is reasonable to expect that the position of the contemporary economic methodology has shifted rightward, closer to the nonlinear and stochastic ends of the map.

Determining the respective methodological positions of mainstream economics before and after the 2007–2009 financial crisis is the topic of the next section.

Analysis of the Economic Literature: Impact of the Recent Financial Crisis

The global 2007–2009 financial crisis came as a surprise not only to laypeople and day-to-day market traders, but also to economists, an intellectual community fully devoted to understanding how the economy works. The crisis was a shock for most mainstream economists, according to whom such huge market imbalances should virtually never happen. Has this dissonance or the increasing critique of the field provided intellectual motivation for some economists to rethink their approach? To investigate this question, we conducted a study of economic papers published by leading economics departments before and after the crisis and searched for any signs of change in economic methods and thinking that might have occurred between the two periods.

According to our analogical cycle and Kuhn's model of scientific revolution, discussed in the Introduction, we expected that the financial crisis would renew the discussion on mainstream analogies and turn attention to alternative analogies that have been largely neglected to date, mainly life sciences analogies. Since our method is designed for studying research papers, which do not contain explicit thematic considerations (Holton, 1996), we could not directly measure the change in the absolute level of analogies. What we measured is the change in the proportion of the type of analogical content in the methodology of the targeted papers. Regarding the direction of change, we reasoned that the crisis would highlight a long-standing criticism of the present-day mainstream economics—that it lacks a deeper

appreciation of holism and “system thinking” (Arthur, 2014; Farmer et al., 2012). Since holism is one of the fundamental principles of life sciences analogies, such as complex adaptive systems, we expected that these analogies would gain more prominence after the crisis, possibly at the expense of mechanistic and thermodynamic analogies. In particular, we expected the principles that characterize biological analogies, such as holism, open systems, discontinuities, nonlinearities, bounded rationality, complexity, and resilience, among others, to get a larger share of attention after the crisis.

Methodology

We compared research output of top economics departments before and after the crisis using two methods: a keyword analysis and a questionnaire study. In what follows we discuss the type of research output we decided to consider, the choice of institutions included in the study, the choice of papers, and the two methods we used to measure the hypothesized change.

Type of output

Since the crisis occurred relatively recently and the processing time of economics journals is very long, we decided to focus on working papers. Working papers are highly regarded as an efficient and common way of exchanging ideas in the economics community. Journal articles have partially lost this function because of the slow reviewing procedures of economics journals. The shorter time gap between the inception of ideas and their public availability as working papers also enabled us to determine the time when ideas occurred more precisely, which was very important for the purpose of our study. We were not concerned about the

credibility of the working papers we analyzed, for at least two reasons. First, we considered only working papers produced at the leading economics departments, renowned for the quality of their work. Second, working papers are intended for publication in journals, and we did not expect the top economists to use one methodology for working papers and another for journal papers. However, a systematic difference in the methodology between the two could occur, given the possibility that papers using alternative methodologies, for instance, are harder to get published. This can happen as editorial boards of journals may reject papers with “inadequate” methodology, keeping them in the category of working papers longer or forcing them to be published elsewhere. While this is an interesting possibility, our goal was to assess if there was a change in ideas in the economist’s mind rather than if the field was ready to accept the change at the institutional level.

Choice of institutions

The literature provides a number of ratings of the academic economics institutions based on different ranking criteria (Kalaitzidakis, Mamuneas, & Stengos, 2011; Kalaitzidakis, Stengos, & Mamuneas, 2003). We opted for the ranking of the Repec repository,³⁷ which is based on aggregation of seven ranking methods³⁸ used to rate economics institutions whose working papers make up their working-paper database. Since our goal was to consider academic papers, from the overall top 10 institutions we discarded two nonacademic institutions, the World Bank Group and the International Monetary Fund. To avoid the problem of double counting papers,

³⁷ Repec is an online repository of publications with the largest database of working papers in economics.

³⁸ A detailed description of the ranking methodology is available online on the Repec website (<https://ideas.repec.org/top/top.inst.alldetail.html>).

we decided to disregard the papers of the National Bureau of Economic Research, whose members are also members of other institutions included in the study. From the remaining seven institutions we ended up with five for which we were able to obtain reliable and comprehensive data. These institutions are the economics departments at the Massachusetts Institute of Technology, Oxford University, and Princeton University, and the Booth School of Business at University of Chicago and the London School of Economics.

Choice of papers

The study included papers that were posted online in the latest pre- and postcrisis years we could select, 2006 and 2013, respectively. To collect the papers we used online databases of the corresponding institutions whenever comprehensive data for 2006 and 2013 were available at their websites. If the data were not available or were incomplete we relied on online repositories such as Repec or Econbiz. In the end, we collected 353 papers, 167 from 2006 and 186 from 2013. After compiling the data we applied two types of analysis to measure and compare indicators of analogy use: a questionnaire and a keyword study.

Questionnaire study

For the questionnaire study we asked authors to assess the use of different analogies in the methodology of their papers (see Appendix). For this purpose we designed questions asking about the use of different thematic positions that indicate specific analogical worldviews. Most of the methodological principles were represented by one question in the questionnaire (Table 2). We decided to omit a question regarding reversibility since the issue is quite technical and difficult to

define briefly with acceptable precision. Similarly, separate questions on the epistemological view and complexity are omitted and considered as a part of the question regarding the use of the complexity approach (Item 13, Table 2). Finally, we explicitly asked authors to assess to what extent they thought their analysis reflected the evolutionary and ecological approaches (Items 11–12, Table 2).

Table 2. Overview of the methodological themata, keywords, and questions

Methodological thema	Keywords	Question
1. Reduction	Marginal, preference, utility, expectation, aggregate, household, consumer, firm, country, good, commodity, representative	Would you say that your paper reflects 1) Strong reductionism 2) Weak reductionism 3) Holism 4) None of the above
2. Isolation	Exogenous, endogenous, entropy, externality, monopoly, oligopoly	How would you characterize analysis in your paper? 1) Partial market analysis 2) General market analysis 3) Open system analysis I ^b 4) Open system analysis II ^b 5) None of the above
3. Reversibility	Path dependence	Since the nature of the issue is very technical we decided not to include this thema in the questionnaire and the keyword study.
4. Dynamic tendency	Equilibrium, supply, demand, price, maximization, optimization, far-from-equilibrium, discontinuity, amplifications, feedback loops, tipping point	In your paper, did you employ 1) Equilibrium analysis 2) Discontinuities and far-from-equilibrium analysis 3) Neither of the above
5. Linearity	Nonlinear, linear,	The model in your paper is 1) Linear 2) Nonlinear 3) Neither of the above
6. Determinism	Probability, distribution, probabilistic, stochastic, noise, random, normal	The model in your paper is 1) Deterministic 2) Stochastic

Methodological thema	Keywords	Question
	distribution, lognormal, power-law	3) Neither of the above The analysis in your paper assumes (multiple options can be selected) 1) Normal distribution 2) Lognormal distribution 3) Power-law distribution 4) Some other distribution 5) None of the above
7. Complexity	See Item 13.	See Item 13.
8. Epistemological view	See Item 13.	See Item 13.
9. Behavioral model	Bounded rationality	Which of the following behavioral strategies are present in your paper (multiple options can be selected)? 1) Maximization without constraints 2) Maximization with constraints 3) Nonmaximizing behavioral strategies 4) None of the above
10. Stability concept	Stability, resilience, robustness, attractor	Which of the following concepts of resilience is reflected in your paper? 1) Engineering resilience 2) Resilience in multi-equilibrium systems 3) Resilience in complex adaptive systems 4) None of the above or not relevant
11. Evolutionary approach	Evolution, dynamics, change, novelty, emergence, self- organization	How much does your paper reflect an evolutionary approach? 1) Not at all 2) A little 3) Quite a lot 4) Very much 5) Inapplicable
12. Ecological approach ^a	Adaptive, system, uncertainty, ecology, environment, complexity, hierarchy, network,	How much does your paper reflect an ecological approach? 1) Not at all 2) A little

Methodological thema	Keywords	Question
	simulation, scenario, agent	3) Quite a lot 4) Very much 5) Inapplicable
13. Complexity approach	Adaptive, system, uncertainty, ecology, environment, complexity, hierarchy, network, simulation, scenario, agent	How much does your paper reflect the ideas of complexity analysis? 1) Not at all 2) A little 3) Quite a lot 4) Very much 5) Inapplicable

^aWe decided to collapse the keywords for the complexity and ecological approaches because of their conceptual similarity. However, they appear as separate questions in the questionnaire.

^bSee Appendix for description.

Note: In addition to 10 themata we asked 3 more questions Items 11, 12, and 13.

As we aimed to assess not only if the principles were employed but also to what extent they were employed, we constructed scales representing different levels of use of the principles. Full descriptions of the concepts used to describe the scale levels are provided in the Appendix. The questionnaire was sent to authors of each selected paper. The advantage of relying on the authors' self-reports is that our raters were well acquainted with the papers and were motivated to be included in the study. Out of 517 authors who received our email, 153 proceeded to the questions, and 97 of them completed the questionnaire fully. Our results are based on the complete entries.

Keyword study

To test our hypothesis more rigorously we also conducted a keyword study. For this purpose, we made a list of keywords that implicitly indicate use of different methodological principles (Table 1). The frequency of keyword appearance served as an indicator of how much a particular principle was involved in the methodology of

the papers. The list of the keywords, in singular and plural form, was organized in subsets, each corresponding to the items (1–13) in Table 2. Due to the conceptual similarities between the ecological and complexity approaches (Items 12 and 13, Table 2), they are represented with the same keywords. Given that keywords could appear in forms other than nouns (e.g., the keyword “emergence” can appear as the adjective “emergent”), we decided to include all words for which the Levenshtein distance from the singular or plural form was equal to or greater than 0.9. The criterion was set conservatively to minimize false alarms, at the expense of some missed signal, that is, undetected keywords. The formula that we used to calculate the Levenshtein distance, $\text{lev}_{a,b}(|a|, |b|)$, between two strings a and b is given as

$$\text{lev}_{a,b}(i, j) = \begin{cases} \max(i, j) & \text{if } \min(i, j) = 0, \\ \min \begin{cases} \text{lev}_{a,b}(i-1, j) + 1 \\ \text{lev}_{a,b}(i, j-1) + 1 \\ \text{lev}_{a,b}(i-1, j-1) + 1_{(a_i \neq b_j)} \end{cases} & \text{otherwise.} \end{cases}$$

Results

First, we present observations from the questionnaire study and discuss changes in the use of each of the methodological principles from the pre- to the postcrisis period. Figure 3³⁹ shows that the use of “strong reductionism” was reduced, whereas “weak reductionism” and especially “holism” became more popular after the crisis.

³⁹ For clarity we decided to omit results for answers “none/neither of the above and inapplicable” in Figures 1–8.

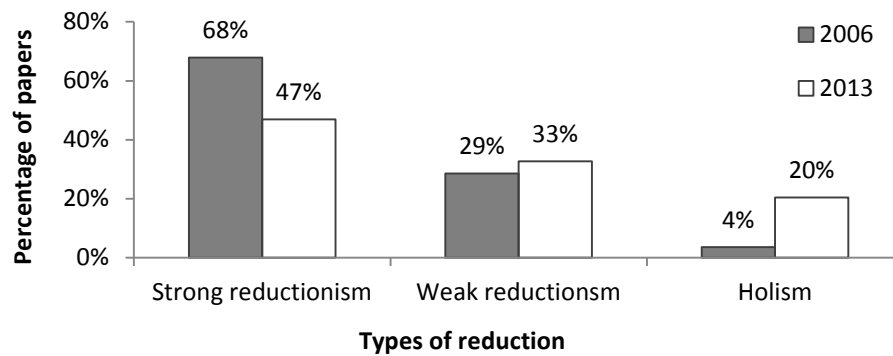


Figure 3. Proportion of reductionist vs. holistic types of analysis in economic methodology based on reports of authors of working papers sampled from 2006 and 2013.

In line with this result we also observed an increased use of “general market analysis” and “open system analysis I”⁴⁰ at the expense of “partial market analysis” (Figure 4). While this indicates a tendency to situate economic phenomena within a broader economic environment, the drop in “open system analysis II”⁴¹ suggests that there was still reluctance to include social or ecological factors as a part of the analysis.

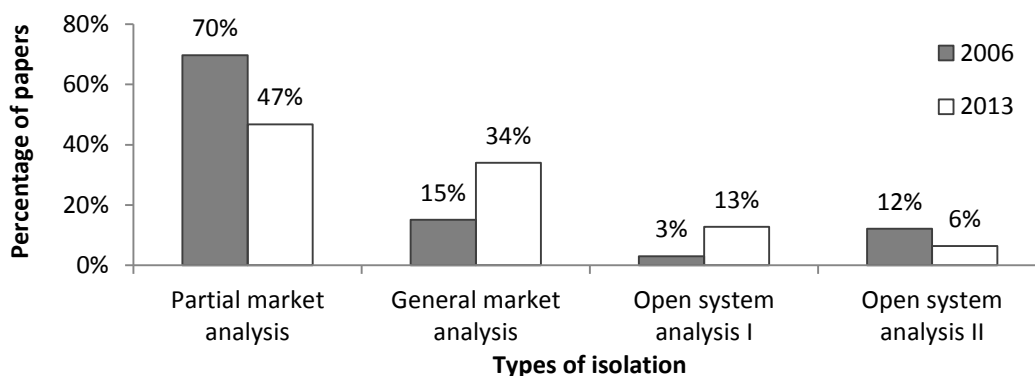


Figure 4. Proportion of isolation versus integration types of analysis in economic methodology based on reports of authors of working papers sampled from 2006 and 2013.

⁴⁰ Open system analysis I is defined as an analysis that is generalized to include interactions of a market space economy with economies from outside the target system (see Appendix).

⁴¹ Open system analysis II is defined as an analysis that is further generalized to include interactions of an open economic system with ecological and/or social factors (see Appendix).

Figure 5 suggests no change when it comes to the use of the equilibrium analysis, which successfully preserved its dominant position in the methodological toolkit of mainstream economists. Regarding stability frameworks used for policy-making recommendations, there were signs of change in favor of perceiving the economy as a complex adaptive system (Figure 6).

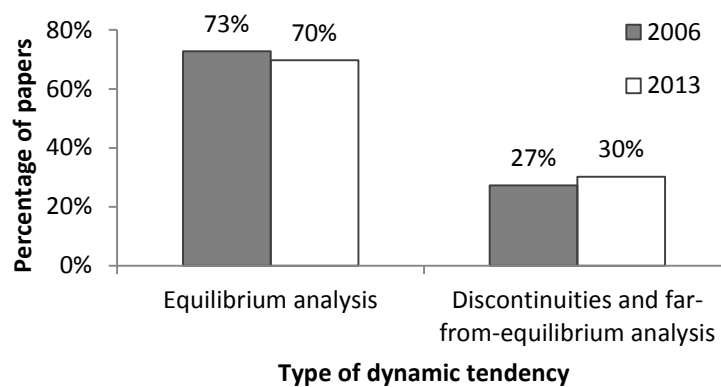


Figure 5. Proportion of equilibrium versus far-from-equilibrium analysis in economic methodology based on reports of authors of working papers sampled from 2006 and 2013.

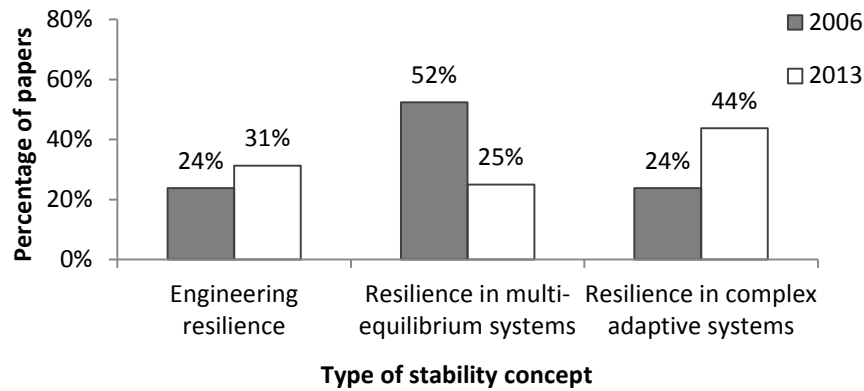


Figure 6. Proportion of different policy-making frameworks in economic methodology based on reports of authors of working papers sampled from 2006 and 2013.

Figure 7 illustrates that when modeling agents' behavior in 2013, economists did not rely as much as before on maximizing decision strategies without constraints. Instead, nonmaximizing behavioral strategies, which were virtually absent from our sample before the crisis, had an important role afterward.

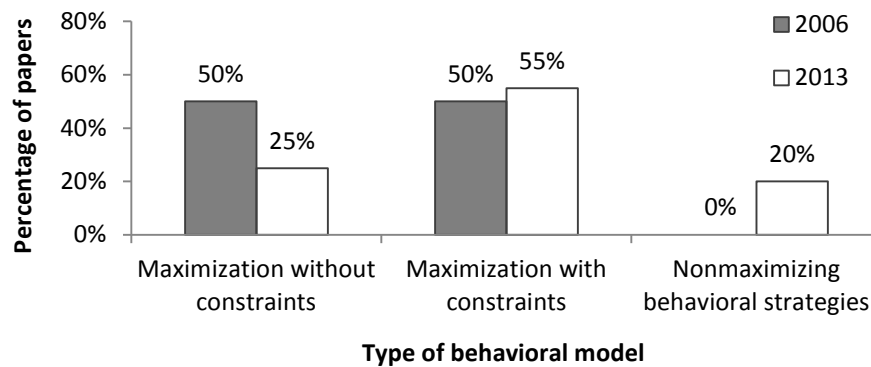


Figure 7. Proportion of different behavioral strategies assumed for modeling of economic agents based on reports of authors of working papers sampled from 2006 and 2013.

Regarding more technical modeling assumptions, there was no negative trend in the use of linear models. In fact the opposite is true (Figure 8). However, the dominance of nonlinear models extended to the postcrisis period.

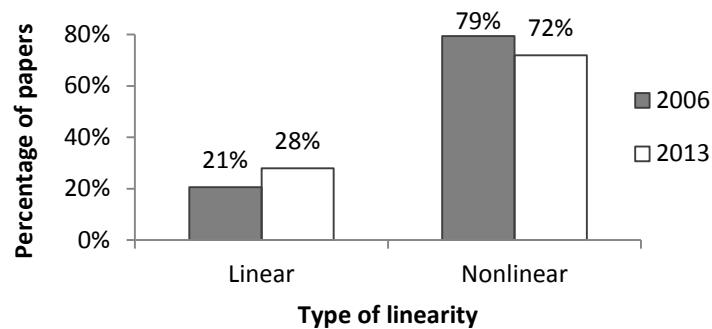


Figure 8. Proportion of linear and nonlinear models in economic methodology based on reports of authors of working papers sampled from 2006 and 2013.

Higher popularity of stochastic models compared to deterministic models before the crisis increased further over the 6-year period (Figure 9). Figure 10 shows that the normal distribution was the most commonly used distribution in economic modeling in both periods, and that lognormal and power-law distributions received slightly more attention in 2013.

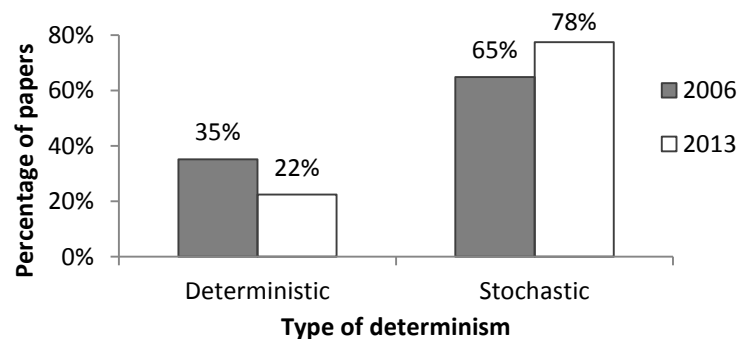


Figure 9. Proportion of deterministic and stochastic models in economic methodology based on reports of authors of working papers sampled from 2006 and 2013.

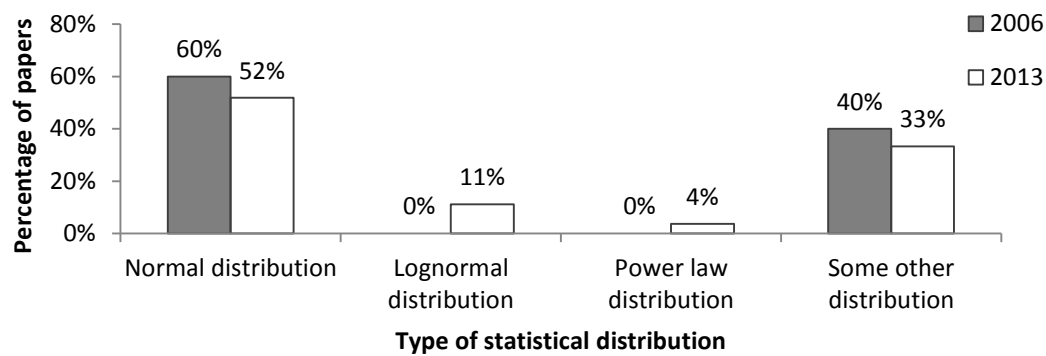


Figure 10. Proportion of different types of distributions in economic models based on reports of authors of working papers sampled from 2006 and 2013.

When authors were asked explicitly how much the methodology in their papers reflected use of evolutionary ideas, the percentage of authors who answered “very much” increased substantially (Figure 11). At the same time the proportion of papers that partially relied on evolutionary concepts showed the opposite trend. It may be that those who experimented with evolutionary ideas before the crisis were encouraged to further explore their use. The answers to the same question regarding complexity and ecological ideas did not indicate any change between the two periods.

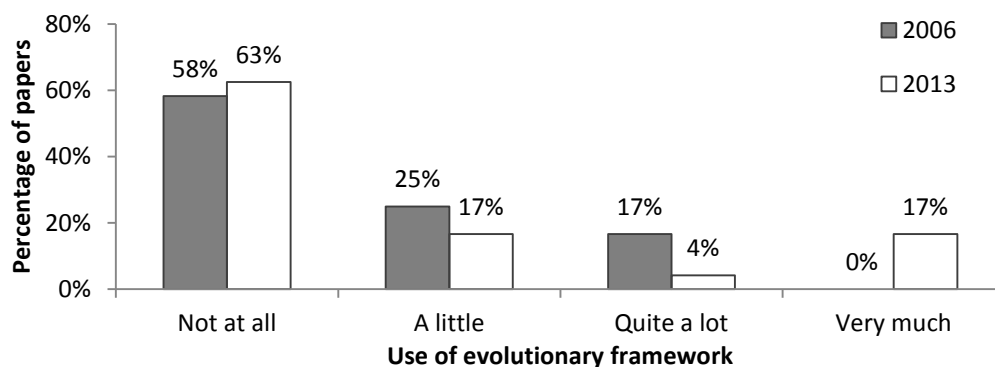


Figure 11. Proportion of different levels of involvement of the evolutionary framework in economic methodology based on reports of authors of working papers sampled from 2006 and 2013.

Figure 12 displays the main results from the keyword study. Figure 12a suggests that almost all top-10 keywords associated with the highest relative change in percentage of papers with those keywords correspond to the life sciences worldview. The roughly doubled use of the keywords network, complexity, and discontinuity is particularly significant since their relative occurrence in the baseline year was at least 5% (Figure 12b).

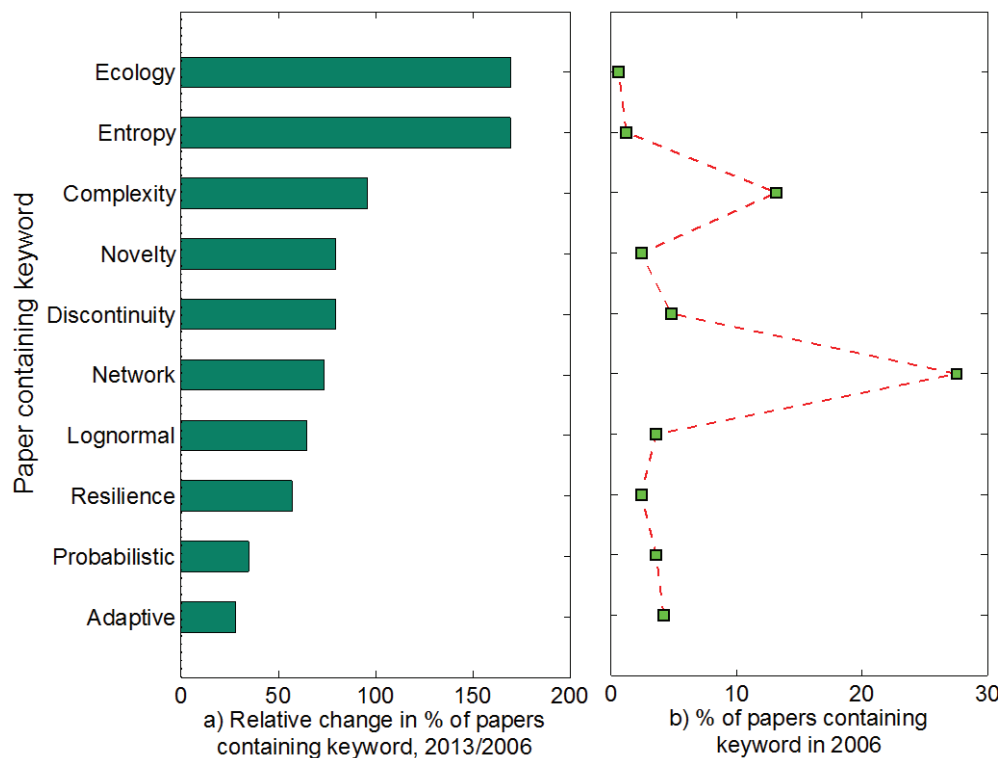


Figure 12. Top 10 keywords. Relative change from 2006 to 2013 in percentage of working papers containing keywords (a), and their relative occurrence in the papers in the baseline year 2006 (b).

Discussion

Economists are polarized about the state of their field. Some have argued that economics is still dominated by neoclassical thought (Earl, 2010; Weintraub, 2007), whereas others have suggested that a new era has already arrived (Holt et al., 2011). The conflicting camps have typically used different criteria: Members of the former

often point out that it is neoclassical theory that is taught in economics departments; the latter, in contrast, have focused on research and cite examples of papers with “heterodox” methodologies published in the mainstream journals authored by scholars affiliated with the top departments. While both arguments are relevant and perhaps correct, it is hard to expect that a significant discrepancy between syllabi and research is sustainable in the long run. The change of syllabi clearly requires more time, but if a sufficient number of scholars conduct insightful research using “novel” methods, these studies will eventually find their way onto the syllabi. This is not to say that the pace of change in economic education is irrelevant, but the main hindrance in understanding whether there is a capacity for such change is lack of evidence about the state of economic research. This study was designed to systematically examine the research of top economic scholars to determine if the 2007–2009 financial crisis facilitated a change in the field.

Our thematic map contains 10 methodological presuppositions, which serve as dimensions in our metric system designed to determine change. This is comparable to Colander, Holt, and Rosser’s (2004) study, in which they defined change in terms of divergence from three methodological positions: rationality, selfishness, and equilibrium. Our results show that important aspects of economic methodology underwent noticeable change after the financial crisis. For instance, authors reported increased use of holistic-oriented approaches, a higher tendency toward more integrative ways of studying economic phenomena, increased popularity of heuristic-like behavioral models, increased use of ecological resilience as a policy-making framework, as well as increased popularity of evolutionary and complexity ideas (Figures 3–11). The increased occurrence of the keywords networks,

complexity, and discontinuity point in the same direction (Figure 12). The use of equilibrium analysis, however, remained at the same level.

We also demonstrated that the benefits of our analogical approach are numerous. First, we used it to provide a rich historical introduction to how the methodological foundations of economics were established. Second, it facilitated identification of distinctive methodological positions, which taken together form consistent methodological worldviews. Third, psychological insights about the underlying processes of scientific discovery made possible the integration of Holton's thematic analysis and Kuhn's theory of scientific revolutions. The solid theoretical framework in turn provided a broader perspective on understanding change in the field and helped form expectations about the direction of change.

Predicting a paradigm shift might be as hard as predicting a financial crisis. Our study demonstrated that signs of change are present, but whether and when they will lead to a paradigm shift it is difficult to tell. Also, it is not clear what the minimal criteria for a paradigm shift are. Perhaps the safest indication that new methodologies have gained wide acceptance is when they find their place in the economics curriculum. So far there is little evidence that this is the case.

Appendix

In what follows, we provide a brief explanation of each of the methodological principles that we used to characterize economic analysis, followed by a question about how much these principles were reflected in the papers.

Reductionism (Strong and Weak) Versus Holism

In economics, reductionism entails explaining a “macro” phenomenon by analyzing the behavior of individual decision makers (agents), such as consumers, households, or firms. Macro phenomena are those that are generated from the collective actions of numerous individuals, such as market price, the unemployment rate, or the gross domestic product.

Here, we differentiate between strong and weak reductionism. Strong reductionism requires that one of the following three criteria be satisfied:

- 1) All agents in a model have a uniform behavioral strategy—for example, maximization of expected utility. In contrast, if a model includes agents with different behavioral strategies, for instance, if in addition to maximizers there are satisficers and/or imitators, then agents are said to have a heterogeneous behavioral strategy. Please note that if agents are maximizing their expected utility with different utility functions the model is still considered to have a uniform behavioral strategy.
- 2) Interactions among agents are not the focus—aside from implicit interactions via market mechanisms, agents’ interactions are not part of the analysis.

- 3) The model is designed top down—this is a property of a model that has macro-level constraints. Assuming an economy is predisposed to achieve a settled state (equilibrium) is an example of a top-down design.

Reductionism that does not possess any of these characteristics is weak reductionism.

In contrast, holism is an alternative to reductionism. It assumes that macro consequences are not explained in terms of individual behavior. Hence, studying macro phenomena by focusing on properties of the whole system, without referring to individual behavior, can be characterized as a holistic approach.

Would you say that your paper reflects

- 1) Strong reductionism
- 2) Weak reductionism
- 3) Holism
- 4) None of the above

Isolation: Closed Versus Open System

Isolation entails separating a phenomenon from its surroundings in order to keep factors that are irrelevant to a particular observation constant. For example, to study the relationship between the prices of two products, isolation would mean keeping the prices of other products that might influence that relationship constant. We distinguish between four levels of isolation in economic analysis, ranging from more closed (1) to more open (4):

- 1) Partial market analysis—analysis is restricted to only a certain segment of a market space (region). Examples are analysis of labor markets or used

car markets in isolation from other sectors (or products, services, etc.) that naturally belong to the same market space.

- 2) General market analysis—analysis aims at an integrative study of a market space economy (which is often hypothetical), in which market segments communicate between each other.
- 3) Open system analysis I—analysis is generalized to include interactions of a market space economy with economies from outside of the target system.
- 4) Open system analysis II—analysis is further generalized to include interactions of an open economic system with ecological and/or social factors.

How would you characterize analysis in your paper?

- 1) Partial market analysis
- 2) General market analysis
- 3) Open system analysis I
- 4) Open system analysis II
- 5) None of the above

Equilibrium Versus Discontinuities and Far-From-Equilibrium Behavior

Economic equilibrium relies on the assumption that individual market actions balance demand and supply and lead to a stable allocation of goods and services on the market. In contrast, analyses of dynamic discontinuities in an economic system are focused on forces that disturb system stability (initiate and facilitate change), for instance, innovations and technological progress, on the one hand, and cheap credit expansions, market bubbles, and collapses of financial markets on the other.

In your paper, did you employ

- 1) Equilibrium analysis
- 2) Discontinuities and far-from-equilibrium analysis
- 3) Neither of the above

Full Versus Bounded Rationality

A fully rational agent is a utility maximizer, able to gather all possible bits of information and integrate them to make optimal decisions. There are two branches of bounded rationality modeling. One branch accepts some agent limitations but essentially preserves maximizing behavior given the acknowledged constraints. Another branch sees limitations as the natural environment of decision makers who, instead of maximizing behavior, have developed adaptive strategies (heuristics) that correspond to given conditions.

Which of the following behavioral strategies are present in your paper (multiple options can be selected)?

- 1) Maximization without constraints
- 2) Maximization with constraints
- 3) Nonmaximizing behavioral strategies
- 4) None of the above

Resilience

Resilience is the stability concept that describes properties of the system state from the perspective of its ability to sustain potential future disturbances. Here, we recognize three different resilience concepts: engineering (single-equilibrium) resilience, resilience in multi-equilibrium systems, and resilience in complex adaptive systems. The concept of engineering resilience recognizes that there is one desired

stability state, and once this is disturbed, typically due to external shocks, the policy intervention goal is to regain the same stability again. The second resilience concept assumes that the system behavior allows for multiple stability states, and that policy recommendations will aim to guide a distressed system through changes in old structures and system organization that lead to new stability states. The last concept treats resilience as a process. Complex adaptive systems tend to exhibit a cyclic behavior with phases characterized by different structural properties and resilience levels. Policy recommendations that offer adaptive guidance of the system through different periods of the cycle imply that this concept is being followed.

Which of the following concepts of resilience is reflected in your paper?

- 1) Engineering resilience
- 2) Resilience in multi-equilibrium systems
- 3) Resilience in complex adaptive systems
- 4) None of the above, or not relevant

Short- Versus Long-Term Horizon

A time horizon of an analysis is considered long if it is longer than 10 years and short if it is any other duration. Additionally, if the time horizon is not explicitly discussed such an analysis is assumed to be timeless. For instance, equilibrium analysis has implicitly a long-term horizon, but given that the time is entirely unspecified, it will be considered as a timeless analysis.

The analysis in your paper has or is

- 1) A short-term horizon
- 2) A long-term horizon
- 3) Timeless

- 4) None of the above

Linear Versus Nonlinear Model

A linear model assumes relationships between variables in the form of a linear function, a polynomial function of degree zero, or one. In contrast, a nonlinear model is one in which dependencies between variables are not expressed as a linear combination. The most common examples are inverse, quadric, exponential, and logarithmic functions.

The model in your paper is

- 1) Linear
- 2) Nonlinear
- 3) Neither of the above

Deterministic Versus Stochastic Model

A deterministic model is one in which the value of a dependent variable is uniquely determined by given values of independent variables and parameters. For the same initial conditions (a set of independent variables and parameters), output of a deterministic model is always the same. This is not the case with stochastic models, whose functional form contains at least one random term whose value is not fully predetermined by initial conditions.

The model in your paper is

- 1) Deterministic
- 2) Stochastic
- 3) Neither of the above

Normal, Lognormal, and Power-Law Distributions

Statistical analyses often assume a particular distribution underlying the data, such as normal distribution.

The analysis in your paper assumes (multiple options can be selected)

- 1) Normal distribution
- 2) Lognormal distribution
- 3) Power-law distribution
- 4) Some other distribution
- 5) None of the above

Complexity

Any analysis that considers some of the common complex adaptive system descriptors, such as nonlinear dynamics, irreversibility, feedback loops, emergence, self-organization, hierarchical (modular) system organization, path dependence, adaptiveness (adaptive systems), and uncertainty can be considered a complex system analysis.

How much does your paper reflect the ideas of complexity analysis?

- 1) Not at all
- 2) A little
- 3) Quite a lot
- 4) Very much
- 5) Inapplicable

Evolutionary Approach

Here, at the center of interest are the evolutionary processes of structural and organizational properties of firms, industries, and economies. Regularities in these processes are studied in the same way that processes of natural selection are

studied in biology, explaining why certain features prevail in the population (economy) and others die out. Innovation, technological progress, entrepreneurship, and creativity are typically recognized as main drivers of change and hence often studied in this context.

How much does your paper reflect an evolutionary approach?

- 1) Not at all
- 2) A little
- 3) Quite a lot
- 4) Very much
- 5) Inapplicable

Ecological Approach

Apart from economic factors, this analysis usually includes environmental and social components that might have important economic consequences. The ecological analysis is an open system analysis, as it considers interactions of the studied market space with its surrounding markets.

How much does your paper reflect an ecological approach?

- 1) Not at all
- 2) A little
- 3) Quite a lot
- 4) Very much
- 5) Inapplicable

3. Contagion in Banking Networks: The Role of Uncertainty^{*}

Abstract. We study the role of information and confidence in the spread of financial shocks through interbank markets. Confidence in financial institutions has only recently been introduced in computational models studying the stability of financial networks (Arinaminpathy et al., 2012). However, so far it has been assumed that all agents have complete information about the system. Here we add realism to a model of interbank markets by introducing uncertainty into what banks know about other banks. In our model, information spreads through the lending network and the quality of information depends on the proximity of the information source. Instead of having complete information, banks receive information that is delayed, noisy, or local. This affects their confidence and the resulting lending decisions. We show that introducing uncertainty leads to a substantial increase in the probability of whole-system collapse after an idiosyncratic bank failure. In contrast, when the same shock is distributed among multiple smaller banks, uncertainty mitigates the impact of the shock. The consequences of a large bank's failure are the most difficult to predict. Our study demonstrates the need for a better understanding of the role of information asymmetries in systemic risk in financial networks.

^{*} I collaborated on a version of this chapter together with Mirta Galesic, Konstantinos Katsikopoulos, Amit Kothiyal, and Nimalan Arinaminpathy.

Introduction

Financial crises are a product of a contagion process. A shock affecting one part of the financial system can spread and reach parts of the system that were not initially affected. In certain conditions, financial difficulties can spread over a large portion of the system, causing prolonged states of distress and low performance. The severity and global character of the 2007–2008 financial crisis demonstrated that modern financial markets are becoming increasingly interconnected and concentrated, two structural changes favoring the chance of far-reaching contagion.

Network approaches offer a useful framework for understanding the dynamics of contagion processes in biological, social, and financial systems (Brockmann & Helbing, 2013; Chmiel, Klimek, & Thurner, 2014; Elliott, Golub, & Jackson, 2014; Gai et al., 2011). By constructing and examining the topology of interdependencies between agents in a system, this approach can be used to model a number of important factors influencing the dynamics of contagion, such as structural properties of the system, properties of agents in the system, triggers of the distress, and contagion mechanisms. In financial systems in particular, individual institutions are linked to each other through a complex system of interbank lending (Minoiu & Reyes, 2013) and holdings in common assets (Caccioli, Shrestha, Moore, & Farmer, 2014). Such a system lends itself naturally to being modeled through a network approach.

There are different mechanisms by which contagion could spread in such a system: for example, counter-party default is a mechanism that spreads financial problems between financial agents with a credit relationship (Acemoglu, Ozdaglar, & Tahbaz-Salehi, 2015). Liquidity hoarding, where institutions withhold funding from one another (which led to the

global “credit squeeze” of 2008), is another form of contagion (Gai & Kapadia, 2010). The system structure determines potential pathways for contagion. For instance, the core–periphery structure of the global banking network makes it easier for financial shocks to reach any part of the system through the well-connected core (Minoiu & Reyes, 2013). In addition to the links between agents, the characteristics of individual agents—such as their risk portfolios—also shape the spread of contagion. All these factors together create a context in which a triggering event, such as failure of a large bank (e.g., Lehman Brothers) or a drop in price of an asset commonly held by many financial agents, initially affects the system. Therefore, a network approach can also help identify events that can be particularly distressing for the system and even anticipate their possible occurrence.

While many models of financial networks treat contagion as being directly transmitted between institutions, it is also widely appreciated that psychological effects, such as market panics, also play a critical role in financial crises (Kelly & Ó Gráda, 2000). Previous work by Arinaminpathy, Kapadia, and May (2012; the AKM model) combined such “confidence effects” with network models in a simple way, presenting a framework where system distress affected how individual institutions responded to their counterparties, and vice versa. For simplicity, this work assumed that institutions have perfect information about the rest of the system (including information about other agents’ capital, loans, deposits, and liquid assets).

In reality, however, uncertainty can play a powerful role in confidence effects. In particular, reporting is not done in real time, the reports are not always fully reliable (e.g., as in the case of Lehman Brothers), all relevant indicators are not included in the reports, and informal channels of communication facilitate further information asymmetries. All of these

factors contribute to the uncertainty of banks' information about the system, and their effects are amplified in times of crisis when changes happen very rapidly.

In the work presented here, we adapted the AKM model to address these issues: we manipulated the distribution of information in a financial system and studied how it influenced banks' decisions. In particular, we modeled information asymmetries as a function of topological distance between information source and information user. When distance increases, information becomes unavailable, delayed, or noisy. We examined the dynamics of the system under each of these conditions.

Confidence, Information, and Financial Contagion

Confidence in Banking Systems

The financial crisis of 2007–2008 is widely recognized as having been a crisis of confidence in financial institutions (Tonkiss, 2009; Uslaner, 2010). A functioning banking network, in which banks borrow and lend money to each other efficiently, is essential for ensuring a liquid banking system and sufficient money supply in the economy. To be efficient and competitive, banks need to invest most of the depositors' funds as lucrative long-term investments and keep only a small fraction as low-profit liquid assets for servicing urgent needs. The stability of this fractional reserve scheme relies heavily on financial participants being confident that deposits will not be withdrawn within a short time and that a sufficient amount of liquid assets can be found at the interbank market if needed.

While this highly efficient system is tolerant of independent actions of agents, synchronized behavior has the potential to destabilize the entire system. For instance, erosion of confidence can lead to collective withdrawals of liquid assets, causing liquidity issues in the financial system that can rapidly spread to the rest of the economy. The potential of confidence to guide collective action is closely related to the dynamics of information in the system. For example, financial agents in different parts of the system have access to different information, leading to an uneven distribution of confidence in the network. Yet, the effect of heterogeneously distributed confidence has been left unexplored due to the assumption of complete information (CI).

CI and uncertainty

The AKM model adopts the CI assumption; that is, it presupposes that agents deterministically and instantly know the exact state of all other agents in the system. In contrast, we modeled information asymmetries that result from information channels being determined by the underlying network of interactions. As a result, banks have partial or imprecise information about other banks in the system.

The assumption that agents have complete information about their economic environment is one of the most prevalent and long-standing assumptions in economic modeling. The CI assumption is typically part of the rational actor model, which additionally assumes rationality of agents. The rational actor is therefore capable of (1) collecting all relevant information (CI assumption) and (2) integrating the collected information and foreseeing all possible states of the world that it implies (rationality). However, real-world economic systems are extremely complex, difficult to measure, and difficult to predict. As Knight (1921) pointed out, much of economic interaction is characterized by deep uncertainty that is hard or impossible to quantify. Therefore, while the rational actor model is applicable to the world of risk, in which potential outcomes and corresponding probabilities are fully known, this is no longer the case in the world of Knightian uncertainty (Aikman et al., 2014; Meder, Le Lec, & Osman, 2013).

Model Overview

Our analysis focuses on a short time horizon, during which the network changes due to the immediate agent's reactions and not due to that agent's strategic decisions. The AKM

model is an agent-based simulation developed in the ecological tradition⁴² to explore the relationship between the structure and the stability of the system (Farmer, 2002; Haldane & May, 2011; May et al., 2008). Agents in the model are banks that are connected by borrowing and lending relationships established at the interbank market. Confidence of agents is modeled as a function of assets and interbank loans remaining in the system. (The lower the level of assets and loans in the system, the lower the confidence of banks.) Decrease in confidence leads to more “defensive” behavior among banks, manifested as shortening of lending maturities or cutting lending altogether (liquidity hoarding). This, in turn, can spread problems to other banks, causing bank failures and a further decrease in confidence. In other words, the model aims to capture dynamic feedback between the macro and micro levels of the system, that is, between the condition of the system (reflected in confidence) and an individual bank’s behavior.

In addition to liquidity hoarding, there are two other contagion mechanisms captured by the model. One relates to the propagation of counterparty credit risk, which can lead to the lender’s default if the borrower is not able to repay the loan. The other is asset price contagion, which takes place when liquidation of assets of failing banks pushes the corresponding asset prices down. All banks that have the same problematic assets in their portfolio will suffer from the price shock (the model does not include correlation between assets).

⁴² In the ecological view, advocated by, among others, Robert May, Andy Haldane, and Doyne Farmer, the complexity of financial markets, which are commonly compared to ecosystems, cannot be captured by looking at their isolated parts but only by putting them together in a more holistic approach. From the ecological perspective, markets are inherently dynamic, and far-from-equilibrium models are much more suitable to describe them than conventional equilibrium models.

Nodes and edges

Nodes or banks in the network can be large or small, the size ratio fixed by the size

coefficient q ($q = \frac{\text{large bank assets}}{\text{small bank assets}}$; the

default value of q in our model is 10).

Banks are represented as simplified

balance sheets (Figure 13). The liability

side contains capital, retail deposits, and

interbank borrowing. The capital level

measures how much stress on the asset

side a bank can withstand before

suffering from a capital default and

becoming insolvent. Retail deposits are

taken to be external to the system and do not play an active role in the model. Interbank

borrowing represents the amount of incoming loans from other banks and the number of

incoming loans represents the in-degree of an individual node. On the asset side there are n

external asset classes, liquid assets, and interbank lending. External asset classes are

distributed among banks from a fixed number G of distinct asset classes contained in the

system. Liquid assets are a small fraction l of the overall assets that banks keep in the most

liquid form to meet immediate needs. They are mostly composed of cash or any cash

equivalent, such as central bank reserves or high-quality government bonds, which are

easily convertible to money. Finally, interbank lending corresponds to outgoing loans to

other banks in the system, thus giving rise to a lending network, as described below.

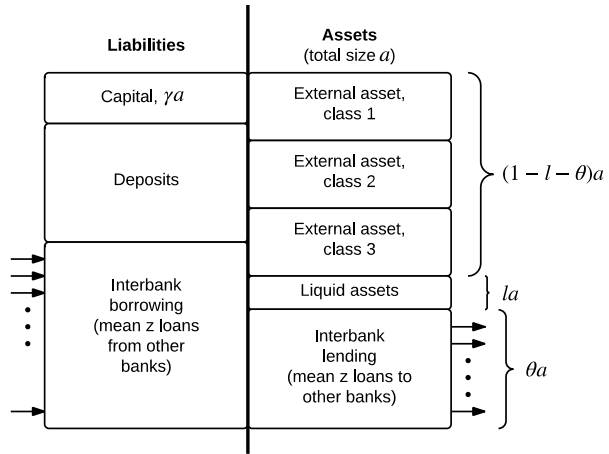


Figure 13. A balance sheet representation of a bank (adapted from Arinaminpathy et al., 2012). a = total assets; γ = capital ratio; l = liquidity ratio; θ = interbank loans-to-assets ratio; z = average number of incoming and outgoing loans.

Parameters γ and θ (Figure 13) determine the initial proportions of capital and interbank loans in the total assets a , respectively.

Network

The network is a directed random graph with N banks. The in-degree and out-degree of banks are determined by a Poisson distribution with parameter z for small banks and $q \times z$ for large banks. Each edge in the network is a loan with direction from lender to borrower. A random half of interbank lending is assigned to be “short-term” and the rest is “long-term” lending. The banks are also interrelated by sharing the same external asset classes. These relationships are the basis for the asset price contagion.

The difference in the connectivity of large and small banks and random assignment of their relationships result in the core–periphery structure of the network. That is, large banks with many links are densely interconnected—forming the core, and small banks with few links are loosely interconnected—forming the periphery. The resulting structure is “shallow,”⁴³ meaning that the average path length in the network is relatively short due to the well-connected core.

Confidence and individual health

Confidence C is the first important determinant of a bank’s behavior. In the AKM model confidence is calculated as a function of A and E , which are measures of solvency and liquidity of the system, respectively:

⁴³ We think that making the network “deeper” would be a valuable exercise. However, the tendency is that the global banking network is getting shallower. It is easier to understand this by envisioning the core–periphery structure of the global banking network. Roughly speaking, because of the high connectivity of the core, any bank at the periphery is either directly connected or one link away from the core, while almost all banks in the core are interconnected.

$$C = AE$$

$$A = \sum_{i=1}^N A_i, \quad E = \sum_{i=1}^N E_i$$

$$A_i = \frac{a_i}{\sum_{i=1}^N a_i^0}, \quad E_i = \frac{e_i}{\sum_{i=1}^N e_i^0}$$

At a given point in time, A denotes the total value of all remaining assets in the system as a proportion of its initial value; E is similarly the fraction of interbank loans not withdrawn from the system; A_i and E_i are the remaining assets and interbank loans of bank i as the proportion of initial value of total assets in the system; a_i and e_i are the absolute values of remaining assets and interbank loans of bank i ; and a_i^0 and e_i^0 are the initial absolute values of assets and interbank loans of bank i .

To calculate C as defined in the AKM model, and to take any action, banks have to know the current and initial values of assets and interbank loans of all banks in the system. To explore how the network behaves in a more realistic setting, especially in times of crisis when the system is changing rapidly, we consider several uncertainty scenarios, described in the following section.

Unlike C , which is a systemic parameter, h_i denotes the individual health of bank i and is calculated as a function of its indicators of solvency c_i and liquidity m_i :

$$h_i = c_i m_i, \quad 0 < h_i < 1$$

$$m_i = \min[1, (A_i^{\text{ST}} + l_i)/L_i^{\text{ST}}]$$

where c_i is the capital of bank i defined as a proportion of its initial value; m_i is the fraction of i 's short-term liabilities that the bank can settle immediately, through its liquid and short-term assets; A_i^{ST} is the total value of i 's short-term interbank assets; L_i^{ST} is the total value of i 's short-term interbank liabilities; and l_i is the amount of liquid assets held by bank i .

Decision rules

There are two possible actions that banks can take in discrete simulation time: shorten long-term interbank loans, and withdraw short interbank loans. Only withdrawing short-term loans can be done in a single time step; shortening long-term loans requires an additional time step. A loan between two banks i and j is, respectively, shortened and withdrawn when

$$h_i h_j < (1 - C) \quad (1)$$

$$h_i h_j < (1 - C)^2 \quad (2)$$

If C is high (1 or close to 1) these conditions are only satisfied under extreme conditions for h_i, h_j . In contrast, a drop in C can cause liquidity hoarding, as this affects the decision conditions of all banks. In addition, the shortening condition is easier to satisfy than the withdrawing condition, which means that banks resort to withdrawal only in relatively urgent situations.

Modeling Uncertainty

We consider three uncertainty scenarios: local information (LI), delayed information (DI), and noisy information (NI). As described in the section presenting model details, the AKM model essentially assumes a CI scenario.

To model uncertainty and determine the amount of information that is included in the calculation of confidence C , we rely on the distance between nodes in the network. The distance $d(i, j)$ is the shortest path length between information user i and information source j . If banks are directly connected, the distance between them is 1. It is also common to say that such nodes are neighbors. The distance between neighbors of neighbors is 2, and so forth. The main principle for modeling uncertainty is that information availability and/or quality deteriorates when the distance from the information source is increased. Once uncertainty is introduced, instead of one common estimate of confidence for all banks ($\forall i: C^i = C$ in the AKM model), each bank has its own individual perception of confidence C^i .

We use the following notation template of any model parameter P : $P_{\text{observed (optional)}}^{\text{time step (optional); observer}}$. For example, a_j^{0i} denotes bank i 's judgment of j 's initial (0 time step) absolute value of assets. Absence of the time step indicator implies the current value of a parameter. The indicator of an observed bank is omitted when a parameter contains no information that relates only to an individual bank, such as C .

In the LI scenario, information is available only up to a certain “interbank” distance. That is, bank i calculates C based on the information about itself and all banks placed within the fixed value of distance d_{\max} . For instance, if $d_{\max} = 1$, then only i and its immediate neighbors contribute information to C . More generally, a bank's confidence is calculated as

$$C^i = A^i E^i$$

$$A^i = \frac{a_i + \sum_{j \in J_i(d_{\max})} a_j^i}{a^{0i}}, \quad E^i = \frac{e_i + \sum_{j \in J_i(d_{\max})} e_j^i}{e^{0i}}$$

$$a^{0i} = a_i^0 + \sum_{j \in J_i(d_{\max})} a_j^{0i}, \quad e^{0i} = e_i^0 + \sum_{j \in J_i(d_{\max})} e_j^{0i}$$

A set $J_i(d_{\max})$ contains all banks that i considers for estimation of C , except for i itself, and is a function of d_{\max} . It is useful to think of d_{\max} as a parameter that determines the reach of i 's perception. To define $J_i(d_{\max})$, we first define the set $J = 1, 2, \dots, N$, which contains all banks in the network. Then, its subset $J_i(d_{\max})$ is defined as

$$J_i(d_{\max}) = \{j \in J \mid d(i, j) \leq d_{\max} \text{ \& } j \neq i\}$$

We consider two versions of the LI scenario: LI1 in which $d_{\max} = 1$ and LI2 in which $d_{\max} = 2$. Since the network is quite shallow (average path length is barely above 2), the latter already contains almost the full graph, and LI3 is equal to CI.

Unlike in the LI scenarios, in the DI scenarios banks receive information from all other banks in the system (d_{\max} is not exogenously set), but some of the information is outdated. We model information delay as a function of distance—the further the information source the longer the delay. Since d_{\max} is determined endogenously by the network structure, it typically takes values not higher than 3 (this is again related to the shallowness of the network). If k denotes the time step when information originated, t the

time step in which it is received, d_s the distance at which delay starts, and s the size of applied delay, then

$$a_j^i = a_j^{kj}, \quad e_j^i = e_j^{kj}$$

$$k = \begin{cases} t & \text{if } d < d_s \\ \max(0, t - s) & \text{if } d \geq d_s \end{cases}, \quad d(i, j) \in \{1, 2, \dots, d_{\max}\}, \quad d_s \in \{1, 2\}, \quad s \in \{1, 2\}$$

We designed four variants of the DI scenario by manipulating s and d_s (Table 3). For instance, in the DI1 and DI3 scenarios the size of the delay is 1 time step ($s = 1$), and in the DI2 and DI4 it is 2 time steps ($s = 2$). In the DI1 and DI2 scenarios delay starts from neighbors of neighbors ($d_s = 2$), whereas in the DI3 and DI4 scenarios it starts immediately from neighbors ($d_s = 1$). We set the minimum value of k to 0 since negative values of time do not make sense in this context.

Table 3. Delay scenarios according to the size of delay (in time steps) assigned to different levels of distance.

Scenario	Size of delay ($t - k$)		
	0 (no delay)	1	2
DI1	$i + \text{neighbors}$	All other banks	
DI2	$i + \text{neighbors}$		All other banks
DI3	i	All other banks	
DI4	i		All other banks

Note. DI = Delayed information; i = information user; k = the time step when information originated; t = the time step in which information is received.

In the NI scenario, noise in information increases with distance. If ε denotes a random error with normal distribution $\varepsilon \sim N(0, \sigma^2)$, v the size of variance in the noise term, and d_{\max} maximal distance in the network, then

$$a_j^i = a_j^j + d\varepsilon, \quad d(i, j) = 1, 2, \dots, d_{\max}, \quad \sigma^2 = v * a_j^j;$$

$$e_j^i = e_j^j + d\varepsilon, \quad d(i, j) = 1, 2, \dots, d_{\max}, \quad \sigma^2 = v * e_j^j;$$

Two variants of the NI scenario are considered: NI5 and NI30. In the former, $v = 5\%$ and in the latter, $v = 30\%$.

Modeling Shocks and Bank Failures

Under each of the conditions described above, we simulated the response of the system to an initial shock. We explored two types of initial shock: (i) a *concentrated* shock (or idiosyncratic shock as in AKM), randomly selecting a large or a small bank and forcing it to fail by setting its capital to zero, and (ii) a *distributed shock*, applied by forcing multiple small banks to fail simultaneously. In particular, a shock of q small banks is equivalent in terms of assets to a large-bank shock. The comparison can be informative in terms of how the system responds if the same shock is concentrated in a single bank or distributed among multiple banks.

A bank can go bankrupt for both liquidity and solvency reasons. A bank i is illiquid if it cannot meet the demand of other banks to repay the loans with its liquid assets and short-term interbank loans $(A_i^{\text{ST}} + l_i)$. A bank i is insolvent once the asset devaluation (from an external asset price decrease or counterparty default, for instance) exceeds its level of capital c_i .

Simulation

If one thinks of the simulation as a set of computational experiments, each replication is one experiment that has two phases. The first phase is to form the network and apply the initiating shock. The second phase is to simulate the propagation of this shock through the network, over several time steps.

Network formation and application of shock

To design a network with in- and out-degree drawn from a Poisson distribution as defined in the AKM model, the procedure requires the random draw to be repeated until the sum of all in-degrees is equal to the sum of corresponding out-degrees (which is a consistency requirement as each edge implies one in- and one out-degree). As a result, draws with nonmatching degrees have to be discarded and degree distributions of successfully acquired networks are effectively generated from a Poisson distribution subset that is not precisely defined. Instead, in the present study we first drew out-degrees from a Poisson distribution and then we used the degree distribution of this draw as weights for conducting weighted random sampling of corresponding in-degrees. This procedure preserves the results of the original AKM model, but has two advantages. First, an analytical analysis of the simulation processes and their outcomes is possible at least in principle, as in- and out-degree distributions of the network are known. Second, it is computationally less expensive, as each network draw is successful. In addition, we used a zero-truncated version of a Poisson distribution that ensured positive values of outgoing interbank loans and provided more balanced initial liquidity of banks. The probability mass function of the zero-truncated Poisson distribution was

$$f(k; z) = P(X = k | k > 0) = \frac{z^k}{(e^z - 1)k!}$$

Once in- and out-degrees were determined it was possible to reconstruct the rest of the bank's balance sheets based on the parameters of the model.

After the network was formed, a shock was applied. The shock hit one or several randomly chosen banks, depending on the type of shock to be applied. The shock was applied in time step 0, before the start of the second phase.

Iteration of actions over time steps

In this phase, five actions were performed in each time step:

- 1) Recalculate health h_i of all banks. The health is used for stipulating liquidation of banks. Zero health implies that a bank needs to be liquidated.
- 2) Liquidate banks that failed in the previous time step (or those failed because of the initial shock). If bank i is to be liquidated then the procedure is as follows:
 - a) Withdraw all short-term loans A_i^{ST} that can be collected from the borrowers of i . Triggering the collection procedure means that i 's borrowers will ask their own borrowers for money, and so forth. Record banks that consequently satisfy the condition of illiquidity and are supposed to be liquidated in the next time step.

- b) Settle all short-term borrowings L_i^{ST} of i that can be paid from its initial liquid assets l_i and collected short-term loans A_i^{ST} . Record the resulting shortage or surplus.
 - c) Calculate the total long-term assets of i by adding long-term loans to the capital c_i . To this sum add the result from substep b. If there is a shortage of assets when the sum is compared to long-term liabilities of i , then i 's long-term lenders suffer from this amount of shock u applied to their capital. The shock is evenly distributed among the lenders, but only up to the level of individual exposures. This ensures that the shock cannot exceed the level of individual lending amount.
 - d) Sell external assets of i , applying the shock to all holders of the same asset classes that i had in its portfolio. The external assets are sold at a market that is taken to be external to the model. The price of asset w is assumed to be decreasing to a fraction $\exp(-\alpha x_w)$ of its initial value (modeled as in AKM), in which x_w is a proportion of the asset w that is sold by i , and α is an indicator of market liquidity that is directly related to confidence C , $\alpha = 1 - C$. If any bank suffers from the capital default based on the shocks from substeps c and d, its health once it is recalculated will be 0. This automatically qualifies such banks for liquidation in the next time step.
- 3) Apply decision rule 2 and withdraw short-term loans if condition is satisfied. It is assumed that loans are perfectly divisible and partial withdrawals are possible. Then, record all banks that become illiquid during the withdrawal in order to be liquidated in the next time step. Note that the second decision rule is applied first as otherwise it would be possible to withdraw long-term loans in a single time step.

- 4) Apply decision rule 1 and administer shortening of long-term loans if the condition is satisfied.
- 5) Recalculate the network and other parameters and go back to step 1 for the next time step.

Model Parameters

The number of banks in the network is $N = 120$. The default value of the size coefficient q is 10, which given other parameters of the model results in a system with $N_b = 11$ large and $N_s = 109$ small banks. For the mean degree, $z = 5$. That is, small banks on average have five incoming and five outgoing loans (edges), while for large banks the average number of loans is 50 ($q * z$). The default value of each single loan is normalized as 1. Small banks have 10, and large banks 20 external asset classes ($n_s = 10, n_b = 20$). Given that on average 10 banks share the same asset class ($g = 10$), this implies 131 distinctive external asset classes ($G = (N_b n_b + N_s n_s) / g$).

The balance sheet's parameters reflect the values observed in the banking sector before the crisis (Bank of England, 2011): the proportion of total assets initially determined to be held in interbank loans $\theta = 0.2$; the proportion of total assets initially liquid $l = 0.01$; and capital to asset ratio $\gamma = 0.04$.

Results

The results are based on 1,000 simulation replications per scenario, with each replication lasting until the system came to rest. Figure 14 demonstrates that the main pattern of results from the AKM model was replicated. The figure depicts the frequency distribution for the total number of banks failing after a shock is applied to a single small (Figure 14a) or a single large (Figure 14b) bank. In the case of a large bank's shock, the fat tail of the distribution indicates that the entire system collapses with a probability of nearly 20%.

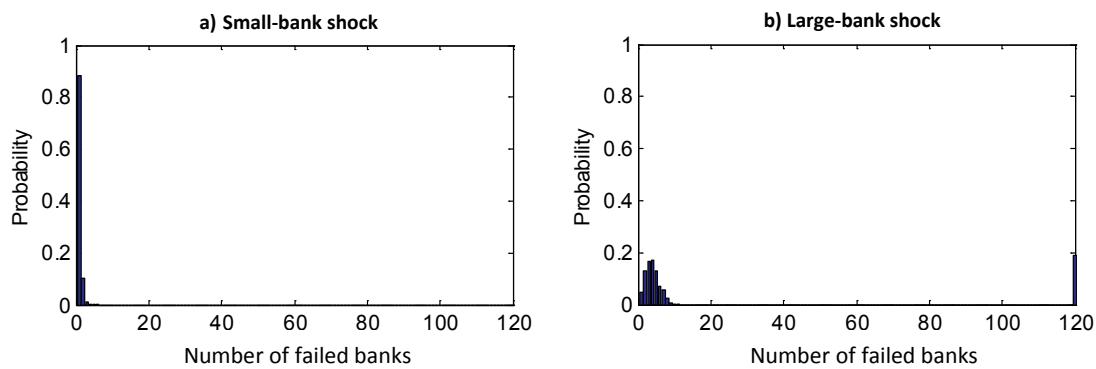


Figure 14. Probability distributions of number of failed banks in a complete information scenario after (a) a shock applied to a small bank and (b) a shock applied to a large bank.

When uncertainty is introduced, the highest impact on the probability distributions of number of failed banks is realized in the LI1 scenario. Figure 15 shows that the probability of whole-system failure after a shock to a single large

bank is now more than 90%. Even after a shock to a small bank there is a nontrivial probability that the entire system fails.⁴⁴

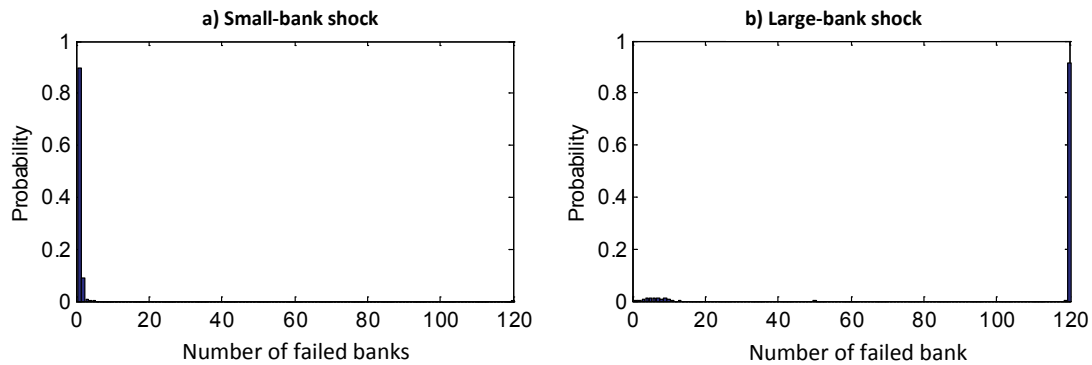


Figure 15. Probability distributions of number of banks failing in the LI1 scenario after (a) a small-bank shock and (b) a large-bank shock. LI1 is a scenario in which a bank has access only to information from its direct neighbors at distance 1. LI = local information.

Figure 16 displays a comparison of probabilities of whole-system failure across different uncertainty scenarios after a centralized (single bank) and a distributed (multiple banks) shock. The probabilities are consistently higher in the distributed than in the single shock treatment, except for in the LI1 scenario. In fact, the LI1 scenario, which is associated with the largest probability of system collapse in the case of a large bank's shock, is at the same time associated with the smallest probability of system collapse in the distributed shock condition.

⁴⁴ In high-resolution data of 10,000 repetitions, the probability of an entire system failing after a small-bank shock increases from 0% in the CK scenario to 0.16% in the LI1 scenario. This is not visible in Figure 15 but is shown in Figure 16.

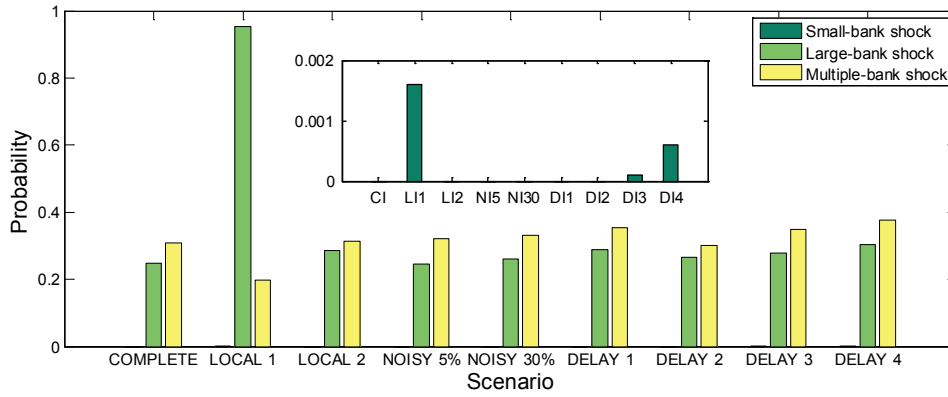


Figure 16. Probability of whole-system failure across different uncertainty scenarios. The superimposed graph is an enlarged representation of the respective probabilities after a small bank's shock. CI = Complete information; LI = local information; NI = noisy information; DI = delayed information. Local 1 and Local 2 = scenarios in which a bank has access only to information at distance 1 and 2, respectively. Noisy 5% and Noisy 30% = scenarios in which noise parameter ν is 5% and 30%, respectively. The delay scenarios are defined in Table 3.

The NI scenarios (regardless of the size of noise) yield similar results to those of the CI scenario. In the case of the DI scenarios, the probabilities of whole-system failure increase with delay. This is even more obvious in the condition with a small-bank shock (see superimposed graph in Figure 16).

In the following section we mainly focus on explaining the most prominent results by comparing the CI and LI1 scenarios. Given that the other uncertainty scenarios (NI and DI) did not produce important difference in results when compared to the CI scenario, we discuss those results very briefly.

Explaining the Results

If the scenarios were mapped onto a diagram showing how much information agents have about others in the system, then the LI1 scenario would be at the opposite end of the spectrum from the CI scenario. Other scenarios would fall close

to CI, as only LI scenarios restrict information availability. The results of the LI1 scenario are particularly striking as they show that a limited information flow further intensifies the contagion dynamics observed in the AKM model after a large-bank failure. In contrast, the LI1 scenario mitigates the impact of a newly designed multiple-bank shock (not applied in the original AKM study⁴⁵) when compared to the CI scenario, in which this treatment in fact yields the highest probability of whole-system failure (Figure 16). While this illustrates that the LI1 scenario does not merely amplify the contagion dynamics irrespective of the initial distress, it also shows how an alternative assumption about information availability can flip the conclusion about which triggering event has the greater potential to cause harm to the system. In what follows we aim at exposing the main factors underlying the observed results.

In the CI scenario, confidence is assessed over the extent of the whole system: while capturing the notion of a generalized psychological environment, this also has the effect of diluting the impact of a localized shock. In the LI1 scenario, by contrast, we have introduced the notion of “locally perceived” confidence that can vary with the neighborhood of different banks. The local impact of an initiating shock is therefore more intense than in a CI scenario but limited to the neighborhood, leaving the confidence of the remaining system initially intact. Yet, this local impact is subsequently transmitted through the system (analogous to the dynamics of crack propagation in a solid medium), resulting overall in a higher risk of system collapse than in the CI scenario. The similarity of the results of the LI2 and CI scenarios (Figure

⁴⁵ The original study includes another type of shock called aggregated shock that also affects multiple banks but it was not designed as a comparison to a large-bank shock (for more details see Arinaminpathy et al., 2012).

16) provides a useful validity check, as the portion of the system taken into account for the confidence estimation is minimally different between the two scenarios.

The same reason applies to the results of the distributed shock treatment, which involves a failure of multiple small banks. While the impacts of the small-bank failures on confidence “add up” in the CI scenario, irrespective of their placement, in the LI1 scenario they independently harm confidences of the disparate localities in which they randomly fall. As a result the probability of whole-system failure after a distributed shock in LI1 is noticeably reduced when compared with the CI scenario (Figure 16). That the “adding-up effect” is less prominent in the LI1 scenario can also be seen if we contrast the results obtained from CI and LI1 after small idiosyncratic and multiple-bank treatments. For this purpose it is useful to interpret a multiple shock as adding extra instances of small shocks to a small shock. The resulting pattern is somewhat counterintuitive. While a small-bank shock alone leads to a higher probability of system failure in the LI1 scenario (than in the CI scenario), after multiple shocks the system fails with a higher probability in the CI scenario.

To further analyze the difference in the results between the CI and LI1 scenarios, we plotted standard deviations of confidence across the scenarios (Figure 17). The standard deviations of the end-state confidence (the system is at rest) were calculated across 1,000 simulation replications, taking into account only the surviving population of banks. Two results stood out. First, standard deviations of confidence were consistently higher after the large concentrated shock than after the distributed shock. The immediate implication is that the outcome of a large concentrated shock is less predictable. Second, there was a large difference between the standard deviations of confidence in the CI and LI1 scenarios. To inspect if this

contributed to the difference in the corresponding results, we carried out an analysis of the role of the confidence variability.

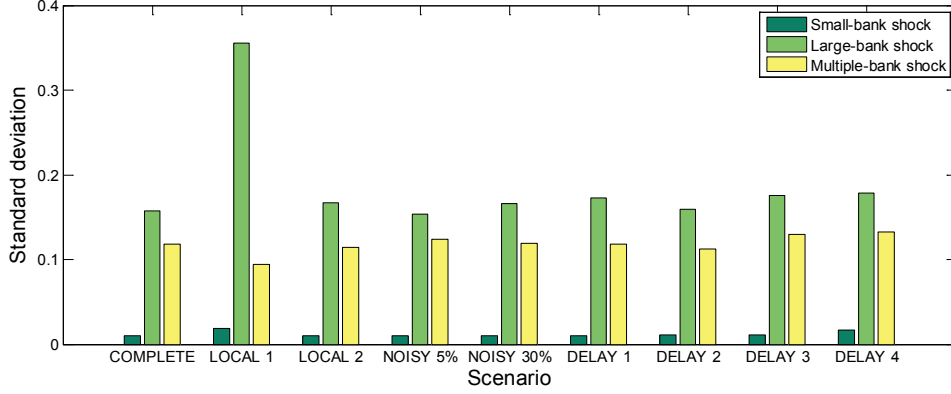


Figure 17. Standard deviations of confidence across all scenarios and three shock treatments: to a small bank, a large bank, and multiple banks. Local 1 and Local 2 = scenarios in which a bank has access only to information at distance 1 and 2, respectively. Noisy 5% and Noisy 30% = scenarios in which noise parameter ν is 5% and 30%, respectively. The delay scenarios are defined in Table 3.

Test 1 – Variability of confidence

We used the analysis to assess the sensitivity of global system indicators, the total assets A and total interbank loans E , to manipulation of the variance of confidence C . A realization of C in a simulation replication is in fact a vector $C(t)$, which contains values of C in different time steps. The manipulation first entailed construction of two vectors $C(t)_{i_{CI}}$ and $C(t)_{i_{LI1}}$ based on data from realizations of C in the CI and LI1 scenarios when a large-bank shock is applied. Two newly composed time sequences of C values were generated from a normal distribution with the same mean and two variances: $C(t)_{i_{CI}} \sim N(C_i^{AV}, V_i^{CI})$, $C(t)_{i_{LI1}} \sim N(C_i^{AV}, V_i^{LI1})$. The mean C_i^{AV} was estimated by averaging the confidence from the realization of the CI scenario over simulation repetitions. The first variance V_i^{CI} was calculated from vectors of global confidence realized in the CI scenario and the second V_i^{LI1} from

vectors of local confidence realized in the LI1 scenario. Finally, the two vectors $C(t)_{i_{CI}}$ and $C(t)_{i_{LI1}}$ were exogenously applied to the CI setting of the simulation (Figure 18). The exogenous application of confidence implies that the calculation of confidence is decoupled from assets and interbank loans in the actual simulation and taken as given. The sequences of realized networks were controlled to be the same in both conditions by setting the same seeding of the random number generator in the simulation.

Even when the timecourse of C is being controlled for, as Figure 18 illustrates, a higher drop of assets and interbank loans corresponds to a higher variance. Unlike in Figure 18a, in Figure 18b curves of A and E sink all the way down to 0. Given that assets and interbank loans determine the level of C by definition ($C = AE$), we designed an additional test to assess the impact of the timecourse of C on the results.

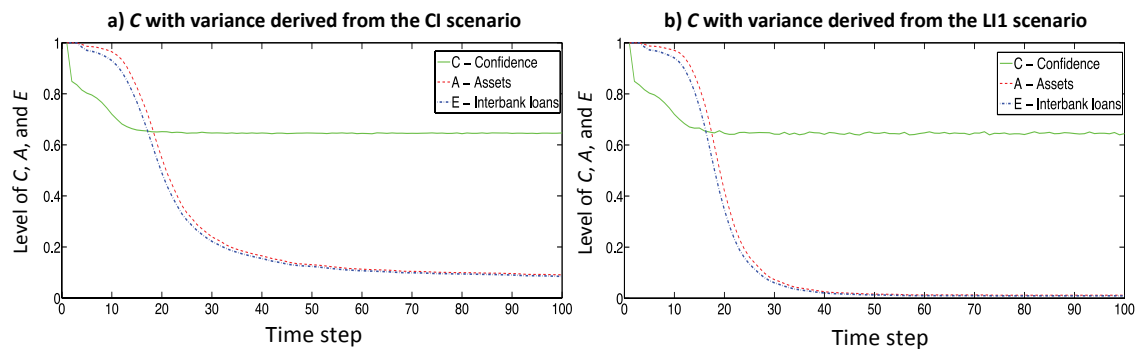


Figure 18. The impact of exogenous manipulation of variance of C on levels of assets and interbank loans across time steps. (a) C with variance V_i^{CI} (derived from the CI scenario). (b) C with variance V_i^{LI1} (derived from the LI1 scenario). CI is a scenario in which a bank has access to information from all other banks in the network. LI1 is a scenario in which a bank has access only to information from banks at distance 1. CI = complete information; LI = local information.

Test 2 – Timecourse of confidence

For this purpose the mean of individual confidences of all banks in the LI1 scenario was calculated and denoted as local confidence. Confidence calculated according to the standard procedure, as in the CI scenario, was denoted global confidence. Figure 19 indicates a steeper decline of local as compared to global confidence when corresponding simulations were performed in an identical simulation setting, that is, when the identically placed large-bank shock was applied to an identical set of networks by controlling the seeding of the random number generator in the simulation.

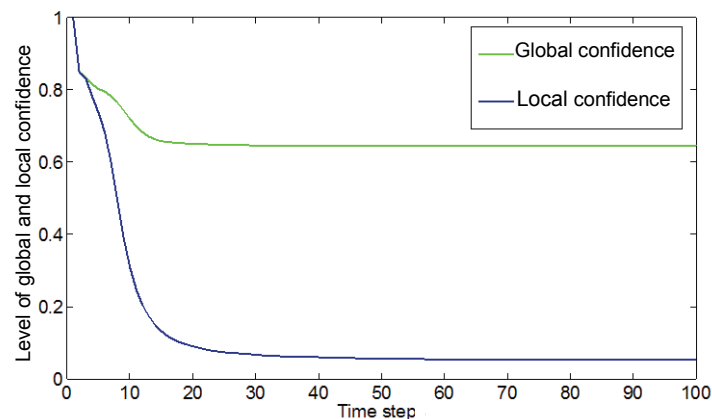


Figure 19. Timecourse of global and local confidence. Global confidence is calculated in a standard way as in the CI scenario. Local confidence is an average of individual confidences of banks in LI1 scenario. CI is a scenario in which a bank has access to information from all other banks in the network. LI1 is a scenario in which a bank has access only to information from banks at distance 1. CI = complete information; LI = local information.

In the next step, we estimated the impact of the observed slope difference between the C curves by exogenous application of the timecourse of local confidence to a hypothetical CI scenario together with the large-bank shock treatment. In the hypothetical scenario, as in the standard CI scenario, all banks in

the system perceive confidence equally, but their perception is no longer endogenously determined. Instead, we forced their global confidence to be equal to previously determined local confidence taken from the realization of the LI1 scenario depicted in Figure 19. This procedure yielded a probability of over 90% of the whole system failing, a result similar to that from the LI1 scenario (Figure 20). The decline of confidence is therefore capable of explaining the difference in the results between the scenarios.

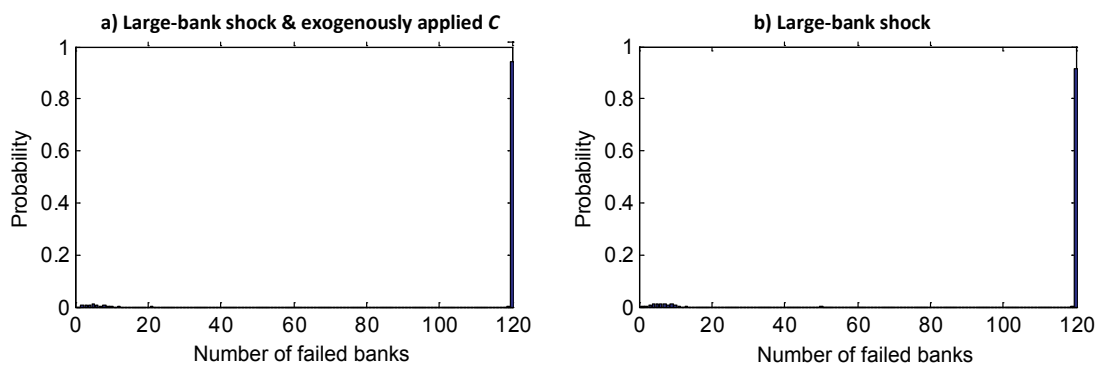


Figure 20. A comparison between probability distributions of number of failed banks after a large-bank shock in the CI (a) and LI1 (b) scenarios when local confidence was exogenously applied to the CI scenario. CI is a scenario in which a bank has access to information from all other banks in the network. LI1 is a scenario in which a bank has access only to information from its direct neighbors at distance 1. CI = complete information; LI = local information.

In the NI scenarios, normally distributed noise averaged out across banks, producing no difference in results compared to the CI scenario (Figure 16). Assuming an alternative distribution of noise would potentially produce more interesting results. On the other hand, the DI scenarios indicate that the delay matters. The result can be accounted for as the effect of overconfidence. Namely, in the DI scenarios, confidence at a particular moment in time was higher than what actual information would imply. This narrows the time window for the preemptive action

that would enable shortening of long-term loans, which otherwise could not be used to meet the upcoming liquidity needs.

Discussion

This study demonstrates that the flow of information in a banking system is highly relevant for the dynamics of market behavior and resulting outcomes. In particular, we introduced uncertainty to a model of a banking network by manipulating accessibility and quality of information available to market participants. While it is clear that both the CI and LI1 scenarios are oversimplifications of reality, our exercise shows how departing from the CI assumption can have a striking impact on the results of the model.

Our main insights are that after uncertainty is introduced, the system becomes far more vulnerable to large-bank failures, as well as that the impact of the large failures becomes less predictable. These findings are further strengthened by our newly design treatment, a multiple-bank shock, suggesting that unlike in the world of CI, in the uncertain world the major threat to the system is posed by the failure of a large bank. Additionally, as a large bank's failure brings many smaller banks down, the multiple-shock treatment can help anticipate the dynamics of a possible second wave of crisis in the system.

The overall results clearly indicate the need to recalculate the price of having large banks in the system and adjust regulation practices accordingly. Well-diversified portfolios of large banks, which reduce the probability of individual failure, have granted them a privileged position with regulators. The resulting

policies designed to ensure safety of individual banks, however, completely ignore systemic risk and the potential of large-bank failures to destabilize the entire system.

The main technical contribution of this study is that we introduced simplified scenarios of alternative information spread in the banking system, relying on the structural properties of the underlying network of interactions. Our results demonstrate that information is a powerful agent of collective market behavior and indicate the need for a better understanding of the channels through which information flows in financial systems. In addition, we clarified events that are taking place in discrete simulation time by defining the time steps precisely. Besides heightened transparency of the underlying assumptions of the model, the clear sequence of events enabled monitoring of system indicators over time. For instance, our timecourse analysis of the confidence was based on this upgrade of the model. We also cast light on the procedure of network design by altering the AKM model slightly to make it more amenable to analysis and save computational time.

Finally, our computational simulation represents an attempt to capture some of the complexity of banking networks even though many important aspects of reality are left out. With information traveling faster and further in the digital age, it can seem that uncertainty is slowly diminishing from the system. Yet, the increasing complexity of the markets that comes with globalization introduces another layer of uncertainty in the system, which might not be immediately obvious. Specifically, any sensible response to information from the market requires an understanding of its implications for other market participants, or even the system as a whole. As a result, the ecology of market behavior, in which decisions are to be made, is becoming increasingly interdependent and complex, making “rational decisions”

even harder to conceive. Capturing the complexity of such interactions requires looking at a sufficiently large portion of the system, which goes far beyond our analytical capabilities. We argue that computational models are a powerful tool that can bring fresh insights to the endeavor of understanding the contagion process in complex systems. Our study is a contribution along these lines.

4. Concentration and Systemic Risk in Banking Networks^{*}

Abstract. Since the 2007–2009 financial crisis, mounting evidence suggests that failures of large banks represent a major risk for the resilience of banking networks. This finding is widely used to link the increasing concentration of financial markets with an increase in their fragility. However, the same argument can easily result in the mistaken idea that any market change associated with an increase in concentration also amplifies systemic risk. In this study we applied stress tests to both hypothetical and empirically calibrated banking networks to observe how various bank-size distributions affect systemic risk. We found that analogous to the resilience of ecosystems, no single property of banking networks could explain the probability of systemic failure. We quantified *concentration* in terms of the Herfindahl–Hirschman index and also identified an additional indicator, *inequality*, measured by Rao’s quadratic entropy, which is important for understanding the concentration–resilience relationship. We found, counterintuitively, that an increase in concentration was beneficial when it was not followed by an increase in inequality. Similarly, a decrease in concentration became harmful when it was not followed by a decrease in inequality. Mergers of large banks increased, whereas mergers of small banks decreased systemic risk. Splitting of large banks was also effective in reducing systemic risk if splitting was not overdone to the extent that it resulted in too many small banks. Our results provide a guideline that can be applied to frequent issues that regulators face, such as bank mergers.

^{*} I collaborated on a version of this chapter together with Mirta Galesic, Konstantinos Katsikopoulos, Amit Kothiyal.

Introduction

Recent literature on the stability of financial systems links the growing concentration of financial networks with the increase in their fragility (Arinaminpathy et al., 2012; Gai et al., 2011; Nier, Yang, Yorulmazer, & Alentorn, 2007). In particular, Nier et al. (2007) showed that when banks in a banking network become larger, a stress test results in the higher probability of systemic failures. Gai et al. (2011) supported findings from ecology and social networks that fat-tailed networks, although robust to random shocks, are particularly vulnerable to targeted shocks, namely, failures of key nodes. Arinaminpathy et al. (2012) reported that systemic risk associated with the failure of a bank does not scale with the bank's size; that is, it increases faster than the size of failed banks. Put simply, when compared to small-bank failures, large-bank failures are more detrimental to the system than what the difference in size would indicate.

The main implication of these studies can be summarized as follows: Because large-bank failures are particularly devastating for the system, the increased presence of large banks is associated with the increased probability of widespread contagion. Extending this to the conclusion that the increased concentration implies increased fragility, we argue, is not substantiated by evidence and may lead to unsound policies. For instance, does the present evidence generate the confidence to design policies based on the assumption that a system always benefits when concentration is reduced?

The global financial network is increasingly complex and there is no single measure that can capture its resilience. The experience of the 2007–2009 financial crisis has focused attention on the concentration of the financial network. In particular, large banks are recognized as perhaps the main culprit of the financial breakdown and significant carriers of

systemic risk. However, the issue becomes less simple if one recognizes that large banks also have a higher capacity to absorb shocks. For instance, compare a large bank facing a financial shock to a few smaller interconnected banks that together have total assets equal to those of the large bank. If a regulation is applied that does not discriminate between banks based on size—say, the relative size of a required safety buffer is equal for large and small banks—then a shock that can be successfully absorbed by the large bank could be fatal for the system of small banks, because knocking out one of them can cause a chain reaction that can eventually bring the remaining banks down. The result, however, depends on many factors, such as the way the small banks are connected and the placement of the shock. This is why computational simulations are a valuable tool for exploring some of those influential factors. The bottom line is that the connection between the size distribution of banks in the network and the network's resilience is not straightforward.

To deal with the problem, we identified two components of systemic risk that are relevant to understanding the concentration–resilience relationship: the *a priori* risk that major idiosyncratic failures (financial shocks) occur in the system, and the *a posteriori* risk that the system will fail as a result of the financial shock. We also precisely defined concentration as measured by the Herfindahl–Hirschman index, which allowed us to manipulate and monitor its levels. We could then demonstrate that an increase in concentration can be beneficial for the system's resilience. In line with our complexity perspective—that it is unlikely that one indicator is capable of explaining the system's resilience—we identified additional indicators. For this purpose we consulted the ecological literature with its long tradition of studying connections between ecological diversity and resilience (Costanza & Kemp, 1994; Costanza, Wainger, et al., 1993). One of these indicators that is particularly important for our study is an indicator of inequality, measured by Rao's

quadratic entropy. In economics, inequality is often confounded with concentration because most of the time they go hand in hand. Yet this is not always the case; for instance, merging two small banks can, depending on the size distribution of the remaining banks in the network, increase the concentration and reduce the inequality of the system at the same time. With the example of a network in which the bank-size distribution is calibrated with empirical data, we showed that when inequality did not follow concentration, an increase in concentration was beneficial for the system's resilience.

In what follows we discuss the decomposition of systemic risk, outline the limitations of previous studies that addressed the concentration–resilience relationship, and present our framework designed to overcome the previous methodological deficiencies. We report our series of computational experiments and finally offer clear policy recommendations based on our results. We conclude with a discussion.

Systemic Risk

Systemic risk is the risk that a major fraction of a financial system ceases to function as a credit provider and collapses (Poledna, Molina-Borboa, Martínez-Jaramillo, van der Leij, & Thurner, 2015; Poledna & Thurner, 2014). In our study we quantified systemic risk in terms of the probability that the whole system would collapse. We also distinguished between two components of systemic risk that can be affected by the distribution of bank sizes in the system: (a) the system's disposition to generate idiosyncratic shocks capable of disturbing the whole system and (b) the system's capacity to absorb shocks. The first relates to the a priori probability that a large disturbance, typically a large bank failure, will occur within the system, and the second to the a posteriori probability that the system will fail as a result of this shock.

The current understanding of the a priori probability does not go much beyond the simple rationale that the more large banks there are in the system, the higher probability that one will fail for an idiosyncratic reason. Previous studies that relied on a stress test as a tool for testing the systemic stability typically assumed that the initial disturbance in the system was sparked by an idiosyncratic bank failure (Arinaminpathy et al., 2012; Nier et al., 2007). If the task is to compare the resilience of systems with different bank-size distributions, a lack of understanding of how the likelihood of an idiosyncratic failure relates to bank size becomes a serious obstacle. Another hindrance is that in practice, this relationship is often blurred by government interventions, particularly those inspired by the policy “too big to fail.” For this reason, the application of random shocks can be used only for rough estimates, as it implies an equal probability of idiosyncratic failures across different bank sizes.

Another important aspect of the problem is that manipulating the size distribution of banks can also affect the a posteriori probability that the system will fail when confronted with a shock. Yet in the design of previous studies (Arinaminpathy et al., 2012; Gai et al., 2011; Nier et al., 2007), the two components of systemic risk were confounded. Therefore, in this study we created a framework in which to examine this particular question, namely, how a change in the bank-size distribution affects the a posteriori probability of systemic failures. The corresponding property quantified by the a posteriori probability we call the *absorbance capacity* of the system. A system with higher absorbance capacity has a smaller risk of systemic failure for a given size of shock. In what follows, we list the main deficiencies of the previous studies in dealing with this question and describe how we designed our framework to avoid these problems.

Limitations of Previous Methodology

Banking networks are often reported as becoming increasingly concentrated; but it is rare that concentration is defined in terms of a comprehensive measure of the distribution of bank sizes. Instead, it is quantified through the fraction of total assets held by large banks, or the pace of growth of the biggest banks in the system (Gai et al., 2011). Although these are reliable indicators of increased concentration, it is difficult to use them to study how fine-grained changes in concentration affect a system's resilience. In previous work the manipulation of concentration was typically simplified. To produce systems that were more concentrated, Nier et al. (2007) enlarged the sizes of the banks proportionally. Arinaminpathy et al. (2012) achieved the same result by varying the ratio of size disparity between the small and large banks in the system. Gai et al. (2011) made a distinction between a random network generated from a Poisson distribution and a fat-tailed network generated from a geometric distribution, which Arinaminpathy et al. (2012) also considered. Given that the present-day banking network has a fat-tailed distribution of bank sizes, policy makers must rely on a finer understanding of the relationship between the size distribution and the system's resilience. Furthermore, in each of the mentioned studies, the manipulation of concentration entailed a change in the size of the shock applied to the system, and in Arinaminpathy et al. (2012) the level of total assets in the system changed as a function of concentration; both can hinder a controlled comparison of systems with different size distributions. Finally, given that the level of concentration does not define the size distribution of a network completely—more than one network can have the same concentration—it is also not clear what other relevant indicators might affect a system's resilience.

The Model

To test the resilience of banking systems, we observed the performance of systems with various size distributions that have been exposed to a large shock. Our measurement of performance is absorbance capacity, quantified as the probability that the whole system will collapse: the lower the probability of systemic failure, the higher the capacity of a system to absorb shocks. Our model of the banking system is a modified version of Arinaminpaty, Kapadia, and May's (2012) model (hereafter, the AKM model).

The AKM model is an agent-based simulation of interbank markets in which agents are banks that borrow and lend money to each other. The banking system is represented as a network whose nodes (vertexes) are banks, and edges (links) are their borrowing and lending relationships. Our modeling of

banks, their relationships, and their behavior corresponds precisely to the AKM model. After presenting the features of the AKM model we adopted in our model, we introduce the changes we

made in the constraints at the system level and describe the administration of the stress test as well as the network structure.

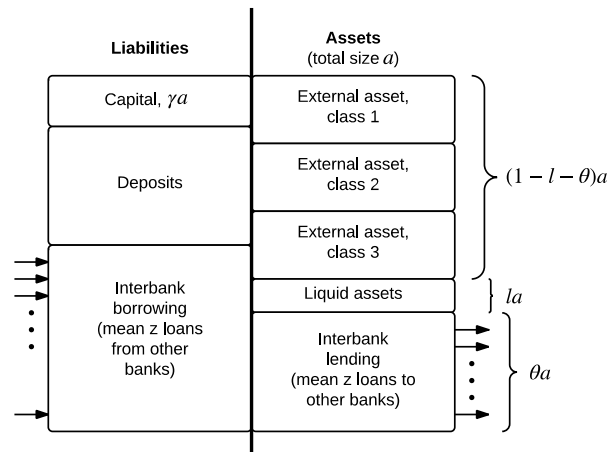


Figure 21. A balance sheet representation of a bank (adapted from Arinaminpathy et al., 2012). a_T = total assets; γ = capital ratio; l = liquidity ratio; θ = interbank loans-to-assets ratio; z = average number of incoming and outgoing loans.

Modeling of banks. Banks are represented as simplified balance sheets (Figure 21).

The liability side contains capital, retail deposits, and interbank borrowing. The capital level measures how much stress on the asset side a bank can withstand before suffering from a capital default and becoming insolvent (this is discussed separately in the section on

modeling of bank failures). Retail deposits are taken to be external to the system and do not play any active role in the model. Interbank borrowing represents the amount of incoming loans from other banks and their number represents the in-degree of an individual node. On the asset side there are n external asset classes, liquid assets, and interbank lending. External asset classes are distributed among banks from a fixed number G of distinct asset classes contained in the system. Liquid assets are a small fraction l of overall assets that banks keep in the most liquid form to meet immediate needs; they are mostly composed of cash or any cash equivalent, such as central bank reserves or high-quality government bonds, which are easily convertible to money. Finally, interbank lending corresponds to outgoing loans to other banks in the system and their number is the out-degree of a node. A random half of interbank lending is assigned to be short-term and the rest is long-term lending.

Modeling bank behavior. Two main determinants of a bank's behavior are its confidence in the system C and its individual health h . In the AKM model confidence is calculated as a function of A and E , which are measures of solvency and liquidity of the system, respectively:

$$C = AE;$$

$$A = \sum_{i=1}^N A_i; \quad E = \sum_{i=1}^N E_i;$$

$$A_i = \frac{a_{Ti}}{\sum_{i=1}^N a_{Ti}^0}; \quad E_i = \frac{e_i}{\sum_{i=1}^N e_i^0}.$$

At a given point in time, A denotes the total value of all remaining assets in the system as a proportion of its initial value; E is similarly the fraction of interbank loans not withdrawn from the system; A_i and E_i are the remaining assets and interbank loans of bank i as the proportion of the initial value of total assets in the system; a_{Ti} and e_i are the absolute values of remaining assets and interbank loans of bank i ; and a_{Ti}^0 and e_i^0 are the initial absolute values of assets and interbank loans of bank i .

Unlike C , which is a systemic parameter, h_i denotes the individual health of bank i and is calculated as a function of its indicators of solvency c_i and liquidity m_i :

$$h_i = c_i m_i; \quad 0 < h_i < 1;$$

$$m_i = \min[1, (A_i^{ST} + l_i)/L_i^{ST}],$$

where c_i is the capital of bank i as a proportion of its initial value, m_i is the fraction of i 's short-term liabilities that the bank can settle immediately through its liquid and short-term assets, A_i^{ST} is the total value of i 's short-term interbank assets, L_i^{ST} is the total value of i 's short-term interbank liabilities, and l_i is the proportion of liquid assets held by bank i .

There are two possible actions that banks can take in the discrete simulation time: shorten long-term interbank loans, and withdraw short interbank loans. Only short-term loans can be withdrawn in a single time step; shortening of long-term loans takes an additional time step. The actions are fully determined by two decision rules:

$$h_i h_j < (1 - C); \quad (1)$$

$$h_i h_j < (1 - C)^2. \quad (2)$$

The shortening action is taken whenever Condition 1 is satisfied, and the withdrawing action is taken whenever Condition 2 is satisfied. There is simple logic behind the rules: If C is high (1 or close to 1) it is less likely that conditions will be satisfied. In contrast, a drop in C can cause liquidity hoarding, as this affects the decision conditions of all banks. In addition, the shortening condition is easier to satisfy than the withdrawing condition, which means that banks resort to withdrawal only in more urgent situations.

The decision rules and the role of confidence in the system reveal the simplicity of the model mechanism. Bank failures lead to a decrease of assets and loans in the system, and the lower the level of assets and loans in the system, the lower the confidence of the banks. A decrease in confidence leads to banks making more conservative decisions that can manifest as shortening of lending maturities or cutting out lending altogether. This, in turn, can perpetuate the tenuous condition of the system, causing bank failures and further dropping of confidence.

System constraints and a stress test. This is where our modifications come into play. Instead of constraining the number of banks in the system, we constrained the size of the system in terms of total assets a_T . The size of the shock S applied to the system was also kept constant and determined as a portion of total assets $S = s * a_T$. The assets allocated for the purpose of shock application S were used to form a bank and the remaining assets $a_R = a_T - S$ to form the rest of the network. We administered the shock by forcing the assigned bank to fail. The rest of total assets a_R are distributed among banks within a range of sizes from the smallest bank with out-degree d_{out} to the biggest bank with out-degree $q * d_{out}$. The size discrepancy indicator q measures how many times the biggest bank is larger than the smallest one; all possible sizes of banks have to fall in between the two.

Modeling of network structure. The network is a directed graph in which each edge is an interbank loan directed from lender to borrower (for convenience, the value of each loan is taken to be 1). To generate the distribution of bank sizes from the assets a_R within the size range set by parameter q , instead of the Poisson distribution used in the AKM model, we used the beta probability density function (PDF) with parameters α and β . Since the proportion of interbank loans θ in the total assets of each bank is fixed, the distribution of out-degrees practically determines the distribution of bank sizes in the system. To determine in-degrees we used the degree distribution of out-degree draws as weights to conduct weighted random sampling of corresponding in-degrees. The banks can also be interrelated if they share the same external asset classes. Those relationships are not represented as edges in the network but they serve as a means of asset price contagion.

The modifications of the AKM model were necessary for our study. It was important to prevent interplay between our manipulation of the size distribution and the level of total assets in the system. All else being equal, increasing the amount of assets in the system increases its ability to absorb shocks of a given size. This is why it is necessary to keep the amount of total assets constant. For the same reason, the size of the initial shock applied to the system must also be kept unchanged. As a result, we administered targeted shocks instead of random shocks. The use of a beta distribution function is justified by its flexibility, which enables easy manipulation of the bank-size distribution, which is essential for the purpose of our study. Finally, the size of the initial shock was calibrated to result in positive values for the probability that the whole system would collapse. Therefore, the initial shock could be relatively large. One might ask if it is reasonable to apply large shocks to a low-concentration system, which does not contain large banks to begin with. In this context, it is useful to think about the initial shock as an experimental device that can take hypothetical

values that help us perform the test. In addition, shocks in real-world banking systems do not have to arise from within the system. A low-concentration system can be affected by large shocks if it, for instance, is connected with external financial markets whose breakdown can transmit financial contagion over its borders; large shocks can also come from outside the financial system.

Indicators of Size Distribution

There is no single indicator that can fully describe the properties of the distribution of bank sizes. Therefore, we used multiple indicators that are typically used to quantify concentration, heterogeneity, and inequality in economic, social, or ecological systems. These concepts are clearly interrelated, as are their corresponding indicators. However, our idea was to observe if any one or a combination of indicators can help explain the accompanying change in absorbance capacity of the system.

The economics literature offers a variety of indicators for measuring *concentration* in the market. Many of these are based on an arbitrary percentage (or number) of the largest market participants while ignoring the rest of the market. The concentration indicator that is, perhaps, the most widely used in the economics literature and practice and is at the same time based on the entire size distribution of market participants is the Herfindahl–Hirschman index (HHI):

$$\text{HHI} = \sum_{n=1}^N p_i^2,$$

where p_i is the market share of a bank (firm) i , and N is the number of banks in the system. The market share of a bank is the proportion of its interbank loans (out-degree) out of all

interbank loans in the system. The index ranges from $1/N$ to 1, and the higher it is, the higher the concentration of the system.

In ecology, on the other hand, there is wide use of indicators that describe the variety of species in an ecosystem. This property is commonly called ecological diversity or *heterogeneity*. If the number of species in an ecosystem is given, then heterogeneity is determined by two factors: their relative availability, and interspecies differences (Twu, Mostofi, & Egerstedt, 2014). The difficulty of measuring the distance between species is the main reason why ecological heterogeneity typically neglects the second factor. An example is the Simpson diversity index (which is equivalent to the HHI) in which the relative availability of species corresponds to the market shares of individual firms. The similarity is intuitive—if markets are dominated by a few market participants then the system is not likely to be very heterogeneous. The Shannon entropy is another widely used heterogeneity indicator also calculated solely from the relative availability of species. In network science, this indicator is commonly denoted the entropy of degree distribution (EDD):

$$\text{EDD} = \sum_i^N p_i \ln p_i.$$

The interpretation of the indicator can be put this way: The more even the participation of available species in a population, the higher the heterogeneity. Another indicator, Rao's quadratic entropy (RQE), additionally takes into account the second factor of heterogeneity—the distance among the species in the population:

$$\text{RQE} = \sum_i^N \sum_j^N p_i p_j d(i, j)^2,$$

where $d(i, j)$, in our case, is the size difference between banks i and j . The RQE specifies that the higher the availability of more distant species, the higher the quadratic entropy. The quadratic entropy adds a novel piece of information to the partial measures of heterogeneity and it is useful to think of it as an indicator of *inequality* in the system.

Compositional diversity combines partial indicators (Ricotta & Marignani, 2007). Here, we consider only separate indicators, as combining the indicators makes interpretation difficult.

We also calculate normalized I' versions of the indicators I with the standard procedure:

$$I' = \frac{I - I_{\min}}{I_{\max} - I_{\min}},$$

where I stands for any of the above indicators; I_{\max} and I_{\min} are maximal and minimal values of corresponding indicators that can be obtained given constraints imposed by other system parameters—for instance, HHI_{\min} and HHI_{\max} are calculated from size distributions that are entirely composed of banks with the minimal and maximal out-degree, respectively.

Simulation Experiments

In what follows we present a series of simulation experiments. Each experiment was based on 1,000 simulation replications and the indicators were calculated as averages across the replications. The first two experiments considered several hypothetical size

distributions. We then constructed a network with a size distribution calibrated with empirical data and conducted further tests to check if our previous observations could be extended to real-world banking networks.

Experiment 1: The skewness of the bank-size distribution

In the first experiment we contrasted the absorbance capacity of two extreme size distributions: one skewed positively, which significantly favors the availability of small banks, and the other skewed negatively, which favors the availability of large banks. The magnitude of skewness is equal in both cases. The uniform distribution is included as a reference point. To simulate the scenarios we used the beta PDF depicted in Figure 22. The bank sizes drawn from the beta distribution, which take values from 0 to 1, could be interpreted as normalized bank sizes. To derive the banks' degree distributions, values obtained from the beta distribution were mapped to a range of available bank sizes determined by the minimal and maximal out-degree of a bank in the system (the default value of the minimal out-degree is 5, and the maximal out-degree is $q * 5$).

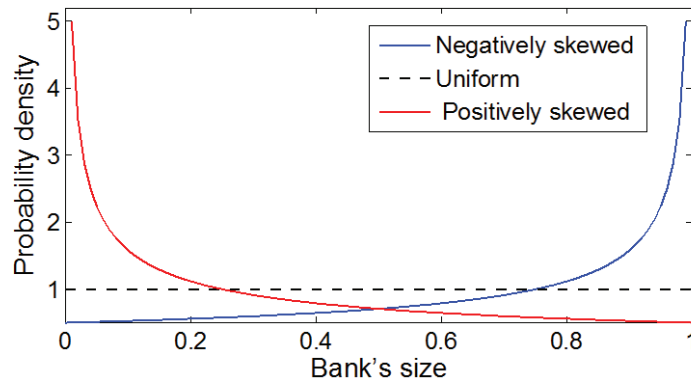


Figure 22. The beta probability density function with parameters a and b . The parameters are set so that the distribution takes three shapes: Negatively skewed (blue; $a = 1$ and $b = 0.5$), uniform (black dashed; $a = 1$ and $b = 1$), and positively skewed (red; $a = 0.5$ and $b = 1$). Note: The values on the x axis can be interpreted as normalized bank sizes. These values are mapped to the preset range of available bank sizes in the system to obtain the banks' degree distributions.

The results of the simulation (Table 4) show that a distribution that favors the availability of large banks (negatively skewed) and is associated with a higher HHI' is also associated with a lower risk of systematic failure. The stable level of RQE' for the two skewed distributions indicates that the degree of inequality is not sensitive to the sign of skewness provided the magnitude of the skewness is equal. As for EDD' , there is no clear linear relationship between the indicator and the absorbance capacity of the system.

Table 4. Manipulation of the skewness of the size distribution

Size distribution	System indicator						
	HHI	EDD	RQE	HHI'	EDD'	RQE'	P_f
Positively skewed	0.02	3.26	353.67	0.53	0.85	0.36	0.93
Uniform	0.02	3.34	332.02	0.63	0.87	0.34	0.45
Negatively skewed	0.03	3.05	355.71	0.77	0.80	0.36	0.16

Note. HHI = Herfindahl–Hirschman index; EDD = entropy of degree distribution; RQE = Rao's quadratic entropy; HHI', EDD', RQE' = normalized indicators HHI, EDD, RQE; P_f = probability of systemic failure.

Experiment 2: The disparity between bank sizes

In the second experiment we manipulated the size distribution without explicitly favoring either small or large banks. For this purpose we compared three symmetric distributions: U-shaped, uniform, and bell-shaped (Figure 23).

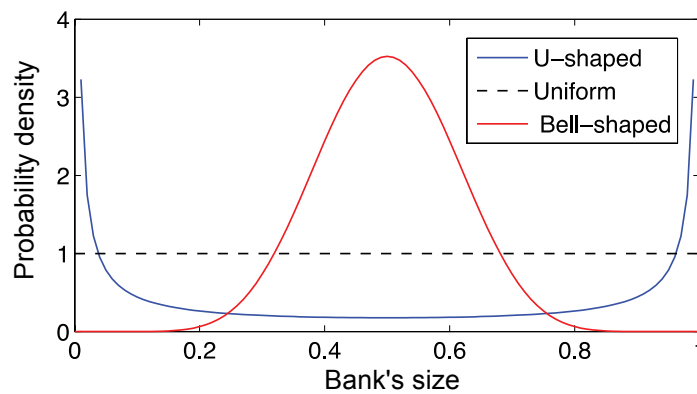


Figure 23. The beta probability density function with parameters a and b . The parameters are set so that three distributions are obtained: U-shaped (blue; $a = 0.1$ and $b = 0.1$), uniform (black dashed; $a = 1$ and $b = 1$), and bell-shaped (red; $a = 10$ and $b = 10$). Note: The values on the x axis can be interpreted as normalized bank sizes. These values are mapped to the preset range of available bank sizes in the system to obtain the banks' degree distributions.

In contrast to the results from Experiment 1, here the distributions associated with a higher HHI' correspond to a higher risk of systemic failure (Table 5). Another important difference is that unlike in the first experiment, the increase in HHI' was accompanied by an even more rapid increase in RQE' .

Table 5. The manipulation of the disparity between the bank's size

Size distribution	System indicator						
	HHI	EDD	RQE	HHI'	EDD'	RQE'	P_f
U-shaped	0.03	2.01	815.35	0.83	0.52	0.83	0.80
Uniform	0.02	3.34	332.02	0.63	0.87	0.34	0.45
Bell-shaped	0.02	2.77	51.84	0.52	0.72	0.05	0.21

Note. HHI = Herfindahl–Hirschman index; EDD = entropy of degree distribution; RQE = Rao's quadratic entropy; HHI', EDD', RQE' = normalized indicators HHI, EDD, RQE; P_f = probability of systemic failure.

The results from Experiments 1 and 2 indicate that the increase in concentration can be beneficial for the system by increasing its absorbance capacity. In contrast, when the increase in concentration was followed by a sharp increase in inequality, the result was the opposite—a drop in the absorbance capacity. This indicates a potentially interesting interplay between HHI' and RQE' in the absorbance capacity. On the other hand, our tests did not reveal a direct correspondence between EDD' and system performance. Therefore, our further analysis was mostly devoted to the analysis of HHI' and RQE'. We next constructed a bank-size distribution calibrated with empirical data to see if the observations from hypothetical distributions have similar implications in a real-world setting. To do so we approximated an empirically parametrized Pareto distribution with a beta distribution, since a beta distribution was more convenient for the manipulation of the indicators required for further analysis.

Approximation of a Pareto Distribution with a Beta Distribution

Arinaminpaty et al. (2012) reported that a Pareto distribution,

$$F(x) = 1 - (x_0/x)^\alpha,$$

defined for $x > x_0$ and $x_0 > 0$, with the scale parameter $\alpha = 0.83$, is the closest fit to the data for the U.S. banking sector in 2011 obtained from the Federal Deposit Insurance Corporation. Since the unbounded Pareto distribution can generate unrealistically large size discrepancies, we used a truncated version of a Pareto distribution with a cumulative distribution function:

$$F_T(x) = \frac{1 - l^\alpha x^{-\alpha}}{1 - (l/h)^\alpha},$$

where $l \leq x \leq h$, and $\alpha > 0$; the upper bound is set to $h = 2,000$ and the lower bound is equal to the minimal bank degree $l = 5$; the value of these two parameters practically imply that the parameter of size discrepancy takes the value $q = 400$.

To approximate $X \sim F_T(x)$ with $Y \sim \text{Beta}(a, b)$ we applied the method of moments. This method requires equating the first and the second moment of the two distributions. Mean and variance of the truncated Pareto distribution are given by

$$E(X) = \frac{l^\alpha}{1 - (l/h)^\alpha} \frac{\alpha}{\alpha - 1} \left(\frac{1}{l^{\alpha-1}} - \frac{1}{h^{\alpha-1}} \right),$$

$$E(X^2) = \frac{l^\alpha}{1 - (l/h)^\alpha} \frac{\alpha}{\alpha - 2} \left(\frac{1}{l^{\alpha-2}} - \frac{1}{h^{\alpha-2}} \right),$$

$$\text{Var}(X) = E(X^2) - E(X)^2.$$

For the given values of parameters l , h , and α , the corresponding values of mean and variance are $E(X) = 43.49$, and $Var(X) = 17,872.30$. Given that the beta distribution takes values in the range of 0 to 1, we normalized X using the standard method:

$$X' = \frac{X - l}{h - l}.$$

The corresponding mean and variance of X' are

$$E(X') = \frac{E(X) - l}{h - l}, \quad Var(X') = \frac{Var(X)}{(h - l)^2}.$$

The obtained normalized values are $E(X') = 0.0193$, and $Var(X') = 0.0045$. As for the beta function, the corresponding moments are

$$E(Y) = \frac{a}{a + b}, \quad Var(Y) = \frac{ab}{(a + b)^2(a + b + 1)}.$$

Now, we can equate the moments:

$$\frac{E(X) - l}{h - l} = \frac{a}{a + b},$$

$$\frac{Var(X)}{(h - l)^2} = \frac{ab}{(a + b)^2(a + b + 1)}.$$

Solving the equations for a and b results in

$$a = \frac{E(X')^2}{Var(X')} (1 - E(X')) - E(X'),$$

$$b = \frac{Var(X')}{E(X')} \left[\frac{(1 - E(X'))E(X')}{Var(X')} - 1 \right] \left[\frac{(1 - E(X'))E(X')}{Var(X')} \right].$$

Assigning the above values to the parameters in the equations gives $a_0 = 0.062$, and $b_0 = 3.151$. Figure 24 displays the truncated Pareto PDF and its beta approximation.

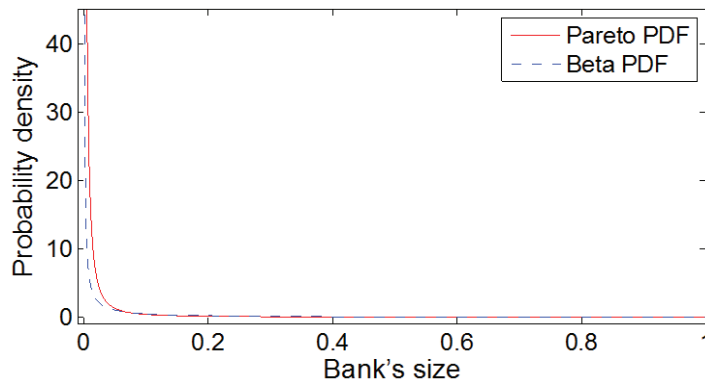


Figure 24. The truncated Pareto probability density function (PDF) with the scale parameter $\alpha = 0.83$ and its approximation with the beta PDF with parameters $a = 0.062$ and $b = 3.151$.

Manipulation of Beta Parameters

In this section we describe our exploration of system behavior in the vicinity of the approximated beta PDF when we performed a fine manipulation of a and b around the determined parameter values $a_0 = 0.062$ and $b_0 = 3.151$. The goal was to observe how the manipulation of the beta PDF in the domain of realistic size distributions affects the

distribution indicators and the corresponding absorbance capacity. In Experiments 3 and 4, we manipulated each of the parameters a and b independently, that is, during the manipulations one of the parameters remained constant.

Experiment 3: Manipulation of parameter b

The manipulation of parameter b in the vicinity of b_0 led to a change mainly in the “tail” part of the beta PDF (Figure 25). In particular, when b went down, the amount of assets contained in the tail inflated—roughly speaking, the size or the number of large banks became bigger on average. As a result there was an increase in HHI' and RQE' . The opposite was true when b went up.

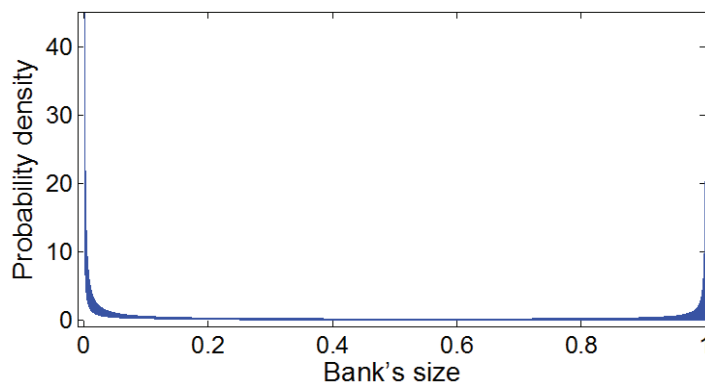


Figure 25. The collection of the beta probability density functions when b takes values in the range bounded by the condition $b_0 + b_0 * (-0.8) \leq b \leq b_0 + b_0 * 0.8$. $b_0 = 3.151$; $a = a_0$.

Table 6. The manipulation of beta parameter b in the vicinity of b_0

Relative change of b	System indicator		
	HHI'	RQE'	P_f
−80%	0.55	0.23	0.47
−40%	0.31	0.06	0.49
−20%	0.26	0.04	0.49
0% ($b = b_0$)	0.22	0.03	0.53
20%	0.19	0.02	0.56
40%	0.16	0.02	0.57
80%	0.13	0.01	0.61

Note. HHI' = Normalized Herfindahl–Hirschman index; RQE' = normalized Rao's quadratic entropy; P_f = probability of systemic failure; $b_0 = 3.151$; $a = a_0$

Experiment 4: Manipulation of parameter a

In contrast to the manipulation of b , which served for exploring the change in the tail part of the size distribution, the manipulation of a largely affected its opposite end (Figure 26). When a increased, the change involved assets held by small banks, so that a number of them migrated toward the center of the size distribution. This led to a moderate increase in HHI' while RQE' remained at essentially the same level (Table 7).

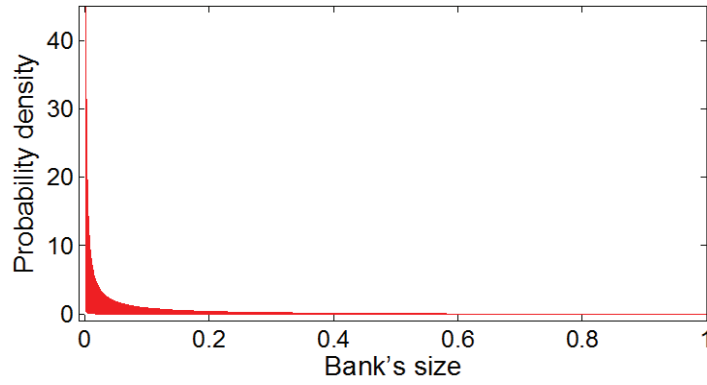


Figure 26. The collection of the beta probability density functions when a takes values in the range bounded by the condition $a_0 + a_0 * (-0.8) \leq a \leq a_0 + a_0 * 0.8$. $a_0 = 0.062$; $b = b_0$.

Table 7. The manipulation of beta parameter a in the vicinity of a_0

Relative change of a	System indicator		
	HHI'	RQE'	P_f
-80%	0.13	0.01	0.98
-40%	0.20	0.02	0.80
-20%	0.20	0.02	0.61
0% ($a = a_0$)	0.22	0.03	0.53
20%	0.23	0.03	0.40
40%	0.23	0.03	0.33
80%	0.24	0.04	0.23

Note. HHI' = Normalized Herfindahl–Hirschman index; RQE' = normalized Rao's quadratic entropy; P_f = probability of systemic failure; $a_0 = 0.062$; $b = b_0$.

The bottom line of both experiments is that an abrupt increase in concentration and inequality produced a small positive effect on the system, whereas a moderate increase in concentration accompanied with a fairly steady level of inequality yielded large benefits for systemic stability. To test if these observations hold in the case of realistic changes in the market, such as bank

mergers or splits, we conducted two more experiments. The additional value of these tests is that they can provide guidance on how regulators should act in such situations.

Experiment 5: Bank mergers

Bank mergers are one of the main causes of the growing concentration in the banking sector (K. D. Jones & Nguyen, 2005). Here, we present a few simple scenarios and their impact on the system indicators (Table 8).

Table 8. The impact of bank mergers on the system indicators

Merger includes	System indicator		
	HHI'	RQE'	P_f
3 largest banks	0.49	0.07	0.94
2 largest banks	0.36	0.05	0.83
0 banks (no merger)	0.22	0.03	0.53
5 smallest banks	0.23	0.03	0.13
10 smallest banks	0.23	0.03	0.11

Note. HHI' = Normalized Herfindahl–Hirschman index; RQE' = normalized Rao's quadratic entropy; P_f = probability of systemic failure.

When the largest banks in the system merged, this led as expected to a considerable increase in concentration and inequality and had an equally negative impact on systemic risk (Table 8). In contrast, the small-bank mergers resulted in a minor increase in concentration and a steady level of inequality, leading to a major reduction in systemic risk.

Experiment 6: Bank splits

Bank splits are not as common as mergers. Here, we provide a few simple scenarios of bank splits as a contrast to the scenarios in Experiment 5 (Table 9). The banks resulting from the splits are assumed to be equal in size.

Table 9. The impact of bank splits on the system indicators

The largest bank splits into	System indicator		
	HHI'	RQE'	P_f
1 bank (no split)	0.22	0.03	0.53
2 banks	0.15	0.02	0.28
3 banks	0.12	0.01	0.21
10 banks	0.08	0.01	0.16
25 banks	0.07	0.00	0.18
50 banks	0.07	0.00	0.41
75 banks	0.07	0.00	0.71
The smallest banks	0.07	0.00	0.98

Note. HHI' = Normalized Herfindahl–Hirschman index; RQE' = normalized Rao's quadratic entropy; P_f = probability of systemic failure.

The results show that splitting the largest bank was beneficial as long as it was associated with a decrease in concentration and inequality (Table 9). When the decrease in concentration stagnated, the positive effects turned negative.

The result from Experiments 5 and 6 confirmed our previous observations that neither concentration nor inequality can be used as a single indicator of systemic risk. For instance, mergers that clearly always lead to an increase in concentration can be beneficial or detrimental to resilience depending on the size of the banks involved in a particular merger. We also observed that the analogous rationale applies to the case of bank splits. In general, whenever a change in the

system led to the migration of assets toward the center of the size distribution, this had positive effects on the absorbance capacity of the system. We observed the same pattern in Experiment 2, in which the bell-shaped distribution “outperformed” the uniform and the U-shaped distribution. Separate tests that are not reported here extended this by showing that the smaller the variance of the bell-shaped distribution, the higher the absorbance capacity of the system. Furthermore, the system is more sensitive to changes in the part of the size distribution with smaller banks. This was first indicated in Experiment 4, in which systemic resilience turned out to be very sensitive to the changes in the small-bank area, and was later confirmed in Experiments 5 and 6, where merging relatively few small banks was very effective in reducing systemic risk, and splitting became progressively harmful when the largest bank was divided into relatively very small banks.

Discussion

Banking networks, like ecological networks, are complex, and there is no single indicator that can explain their resilience. In this study we debunked a simplified view of the relationship between concentration and resilience. We summarize our main findings as follows: Given the current state of banking networks, a decrease in concentration will not always lead to an increase in stability; an increase in concentration turned out to be beneficial when it was not followed by an increase in inequality; analogously, a decrease in concentration became harmful when it was not followed by a decrease in inequality; mergers of large banks are detrimental, whereas mergers of small banks are beneficial for systemic resilience; splitting of large banks is also effective in reducing systemic risk if splitting is not

overdone to the extent that it results in too many small banks. Our results provide a useful guideline for policy makers that can help in dealing with frequent market changes such as mergers.

The main caveat is that our study does not address how the bank-size distribution affects the a priori probability that triggering events will occur in the system. However, in this respect our findings, such as those related to mergers of large banks, are not in conflict with previous studies that have identified large banks as major carriers of systemic risk—because if they fail, the entire system may suffer. Here, we demonstrated that an increased concentration in the part of the size distribution taken up by small banks could, in fact, be beneficial for systemic stability. Further, the decomposition of systemic risk can lead to a better understanding of its individual components before they are reintegrated.

There is no reason to doubt that the challenge of arriving at a better understanding of financial networks is similar to that faced by ecologists who had to explore a variety of indicators in order to advance the understanding of the resilience of ecological systems. Our contribution along these lines is that we have shown that an additional indicator, inequality, can help elucidate how the size distribution in a banking system affects its systemic risk. Therefore, it would not be surprising if further progress is made by including additional indicators.

References

- Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic Risk and Stability in Financial Networks. *American Economic Review*, 105(2), 564–608.
<http://doi.org/10.3386/w18727>
- Aikman, D., Galesic, M., Gigerenzer, G., Kapadia, S., Katsikopoulos, K. V, Kothiyal, A., ... Neumann, T. (2014). *Taking uncertainty seriously: simplicity versus complexity in financial regulation* (No. 28). *Bank of England Financial Stability Paper*.
- Albert, R. (2005). Scale-free networks in cell biology. *Journal of Cell Science*, 118(21), 4947–4957. <http://doi.org/10.1242/jcs.02714>
- Albin, P. S., & Foley, D. K. (1998). *Barriers and bounds to rationality: Essays on economic complexity and dynamics in interactive systems*. Princeton, NJ: Princeton University Press.
- Alchian, A. (1950). Uncertainty, evolution and economic theory. *Journal of Political Economy*, 58, 211–221.
- Allen, C. R., & Holling, C. S. (2008). *Discontinuities in ecosystems and other complex systems*. New York, NY: Columbia University Press.
- Allen, T. F. H., & Starr, T. B. (1982). *Hierarchy: Perspectives for ecological complexity*. Chicago, IL: University of Chicago Press.
- Alvey, J. E. (1999). *Mechanical analogies in Adam Smith* (Discussion Paper No. 99). Wellington, NZ: New Zealand Institute of Economic Research.
- Anderson, J. R., Fincham, J. M., & Douglass, S. (1997). The role of examples and rules in the acquisition of a cognitive skill. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 23(4), 932–945.
- Anderson, P. W. (1972). More is different. *Science*, 177(4047), 393–396.

<http://doi.org/10.1126/science.177.4047.393>

Arinaminpathy, N., Kapadia, S., & May, R. M. (2012). Size and complexity in model financial systems. *Proceedings of the National Academy of Sciences of the United States of America*, 109(45), 18338–43. <http://doi.org/10.1073/pnas.1213767109>

Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal*, 99(394), 116–131. <http://doi.org/10.2307/2234208>

Arthur, W. B. (2014). *Complexity and the economy*. New York, NY: Oxford University Press.

Arthur, W. B., Durlauf, S. N., & Lane, D. (1997). Introduction: Process and emergence in the economy. In W. B. Arthur, S. N. Durlauf, & D. A. Lane (Eds.), *The economy as an evolving complex system II*. (pp. 1– 14). Reading, MA: Addison-Wesley.

Ashby, R. W. (1947). Principles of the self-organizing dynamic system. *Journal of General Psychology*, 37, 125–128.

Bank of England. (2011). *Instruments of macroprudential policy*. *Bank of England Discussion Paper*. Retrieved from <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Instruments+of+macroprudential+policy#3>

Barabási, A.-L., Jeong, H., Neda, Z., Ravasz, E., Schubert, A., & Vicsek, T. (2002). Evolution of the social network of scientific collaboration. *Physica A*, 311, 590–614. [http://doi.org/10.1016/S0378-4371\(02\)00736-7](http://doi.org/10.1016/S0378-4371(02)00736-7)

Barker, R. G. (1968). *Ecological psychology: Concepts and methods for studying the environment of human behavior*. Stanford, CA: Stanford University Press.

Battiston, S., Farmer, J. D., Flache, A., Garlaschelli, D., Haldane, A., Heesterbeek, H., ... Scheffer, M. (2016). Complexity theory and financial regulation. *Science*, 351(6275), 818–819.

- Beinhocker, E. D. (2006). *The origin of wealth: Evolution, complexity, and the radical remaking of economics*. Boston, MA: Harvard Business School Press.
- <http://doi.org/10.1057/eej.2008.5>
- Berkes, F., & Folke, C. (1998). Linking social and ecological systems for resilience and sustainability. In F. Berkes & C. Folke (Eds.), *Linking social and ecological systems: Management practices and social mechanisms for building resilience* (Vol. 1, pp. 13–20). Cambridge, England: Cambridge University Press. Retrieved from <http://books.google.com/books?hl=fr&lr=&id=XixuNvX2zLwC&pgis=1>
- Binmore, K. G. (2009). *Rational decisions* (The Gorman). Princeton, NJ: Princeton University Press. http://doi.org/10.1007/3-540-27503-7_4
- Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, 81(3), 637–654. <http://doi.org/10.1086/260062>
- Bogdanov, A. (1980). *Essays in tektology: The general science of organization* (G. Gorelik, Trans.). Seaside, CA: Intersystems Publications.
- Bollerslev, T. (2010). Glossary to ARCH (GARCH). In T. Bollerslev, J. R. Russell, & M. W. Watson (Eds.), *Volatility and time series econometrics: Essays in honor of Robert Engle* (pp. 137–163). Oxford, England: Oxford University Press.
- <http://doi.org/10.1093/acprof:oso/9780199549498.003.0008>
- Bollerslev, T., Chou, R. Y., & Kroner, K. F. (1992). ARCH modeling in finance. A review of the theory and empirical evidence. *Journal of Econometrics*, 52, 5–59.
- [http://doi.org/10.1016/0304-4076\(92\)90064-X](http://doi.org/10.1016/0304-4076(92)90064-X)
- Boulding, K. E. (1966). The economics of the coming spaceship Earth. In H. Jarrett (Ed.), *Environmental quality in a growing economy. Essays from the Sixth RFF Forum* (pp. 1–8). Baltimore, MD: Johns Hopkins University Press.

<http://doi.org/10.4324/9781315064147>

Brainard, W. C., & Scarf, H. E. (2005). How to compute equilibrium prices in 1891. *American Journal of Economics and Sociology*, 64(1), 57–83.

Brock, W. A., & Malliaris, A. G. (1989). *Differential equations, stability and chaos in dynamic economics*. Amsterdam, the Netherlands: North-Holland.

Brockmann, D., & Helbing, D. (2013). The hidden geometry of complex, network-driven contagion phenomena. *Science (New York, N.Y.)*, 342(6164), 1337–1342.

<http://doi.org/10.1126/science.1245200>

Bromley, D. W. (2008). Sustainability. In *The new Palgrave dictionary of economics* (2nd ed.). New York, NY: Palgrave Macmillan.

Caccioli, F., Shrestha, M., Moore, C., & Farmer, J. D. (2014). Stability analysis of financial contagion due to overlapping portfolios. *Journal of Banking & Finance*, 46, 233–245.

<http://doi.org/10.1016/j.jbankfin.2014.05.021>

Chan, J., Paletz, S. B. F., & Schunn, C. D. (2012). Analogy as a strategy for supporting complex problem solving under uncertainty. *Memory & Cognition*, 40, 1352–1365.

<http://doi.org/10.3758/s13421-012-0227-z>

Chmiel, A., Klimek, P., & Thurner, S. (2014). Spreading of diseases through comorbidity networks across life and gender. *New Journal of Physics*, 16.

<http://doi.org/10.1088/1367-2630/16/11/115013>

Cochrane, J. H. (2011). How did Paul Krugman get it so wrong? *Economic Affairs*, 31(2), 36–40. <http://doi.org/10.1111/j.1468-0270.2011.02077.x>

Cohen, I. B. (1994). *Interactions: Some contacts between the natural sciences and the social sciences*. Cambridge, MA: Cambridge University Press.

Colander, D. (2010). The economics profession, the financial crisis, and method. *Journal of*

Economic Methodology, 17(4), 419–427.

<http://doi.org/10.1080/1350178X.2010.525039>

Colander, D., Goldberg, M., Haas, A., Juselius, K., Kirman, A., Lux, T., & Sloth, B. (2009). The financial crisis and the systemic failure of the economics profession. *Critical Review*, 21(2-3), 249–267. <http://doi.org/10.1080/08913810902934109>

Colander, D., Holt, R., & Rosser, B. (2004). The changing face of mainstream economics. *Review of Political Economy*, 16, 485–499.

<http://doi.org/10.1080/0953825042000256702>

Colander, D., Howitt, P., Kirman, A., Leijonhufvud, A., & Mehrling, P. (2008). Beyond DSGE models: Toward an empirically based macroeconomics. *American Economic Review*, 98(2), 236–240. <http://doi.org/10.1257/aer.98.2.236>

Common, M., & Perrings, C. (1992). Towards an ecological economics of sustainability. *Ecological Economics*, 6(1), 7–34. [http://doi.org/10.1016/0921-8009\(92\)90036-R](http://doi.org/10.1016/0921-8009(92)90036-R)

Costanza, R. (1996). Ecological economics: Reintegrating the study of humans and nature. *Ecological Applications*, 6(4), 978–990. <http://doi.org/10.2307/2269581>

Costanza, R., & Kemp, M. (1994). Predictability, scale, and biodiversity in coastal and estuarine ecosystems: Implications for management. *Biological Conservation*, 67(2), 280. [http://doi.org/10.1016/0006-3207\(94\)90629-7](http://doi.org/10.1016/0006-3207(94)90629-7)

Costanza, R., Kemp, M., & Boynton, W. R. (1993). Predictability, scale, and biodiversity in coastal and estuarine ecosystems: implications for management. *Ambio*, 22, 88–96. [http://doi.org/10.1016/0006-3207\(94\)90629-7](http://doi.org/10.1016/0006-3207(94)90629-7)

Costanza, R., Wainger, L., Folke, C., & Mäler, K. G. (1993). Modeling complex ecological economic systems: Toward an evolutionary, dynamic understanding of people and nature. *BioScience*, 43(8), 545–555. Retrieved from

<http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Modeling+Complex+Ecological+Economic+Systems+Toward+an+evolutionary+,+of+people+dynamic+understanding+and+nature#0>

Cyert, R. M., & March, J. G. (1963). *A behavioral theory of the firm*. Englewood Cliffs, NJ: Prentice-Hall. <http://doi.org/10.2307/2228147>

Daly, H. E. (1968). On economics as a life science. *Journal of Political Economy*, 76, 392–406.

Di Matteo, T., Aste, T., & Dacorogna, M. M. (2005). Long-term memories of developed and emerging markets: Using the scaling analysis to characterize their stage of development. *Journal of Banking and Finance*, 29(4), 827–851. <http://doi.org/10.1016/j.jbankfin.2004.08.004>

Dunbar, K. (1997). How scientists think: On-line creativity and conceptual change in science. In T. B. Ward, S. M. Smith, & J. Vaid (Eds.), *Creative thought: An investigation of conceptual structures and processes* (pp. 365–395). Washington, DC: American Psychological Association.

Earl, P. E. (2010). Economics fit for the Queen: A pessimistic assessment of its prospects. *Prometheus*, 28(3), 209–225. <http://doi.org/10.1080/08109028.2010.511773>

Egerton, F. N. (2007). A History of the ecological sciences, Part 23: Linnaeus and the economy of nature. *Bulletin of the Ecological Society of America*, 88(1), 72–88. <http://doi.org/10.1890/0012-9623-91.1.21>

Elliott, M., Golub, B., & Jackson, M. O. (2014). Financial networks and contagion. *American Economic Review*, 104(10), 3115–3153. <http://doi.org/10.1257/aer.104.10.3115>

Ellison, G. (2002). The slowdown of the economics publishing process. *Journal of Political Economy*, 110(5), 947–993. <http://doi.org/10.1086/341868>

Epstein, J. M., & Axtell, R. (1996). *Growing artificial societies from the bottom up*.

Cambridge, MA: MIT Press.

Fagerberg, J. (2002). *A layman's guide to evolutionary economics* (TIK Working Paper No.

17). Oslo, Norway: Centre for Technology, Innovation and Culture.

Farmer, J. D. (2002). Market force, ecology and evolution. *Industrial and Corporate Change*,

11(5), 895–953. <http://doi.org/10.1093/icc/11.5.895>

Farmer, J. D., Gallegati, M., Hommes, C., Kirman, A., Ormerod, P., Cincotti, S., ... Helbing, D.

(2012). A complex systems approach to constructing better models for managing

financial markets and the economy. *European Physical Journal: Special Topics*, 214(1),

295–324. <http://doi.org/10.1140/epjst/e2012-01696-9>

Farmer, J. D., & Geanakoplos, J. (2009). The virtues and vices of equilibrium and the future

of financial economics. *Complexity*, 14(3), 11–38. <http://doi.org/10.1002/cplx.20261>

Farmer, J. D., Shubik, M., & Smith, E. (2005). Is economics the next physical science? *Physics*

Today, 58(9), 37–42.

Farmer, J. D., Smith, E., & Shubik, M. (2005). Economics: The next physical science? *System*,

(1520), 9. <http://doi.org/10.1063/1.2117821>

Fisher, I. (1892). *Mathematical investigations in the theory of value and prices*. New Haven,

CT: Neudruck.

Forrester, J. W. (1958). Industrial dynamics. *Harvard Business Review*, 36(4), 37–66.

Gai, P., Haldane, A., & Kapadia, S. (2011). Complexity, concentration and contagion. *Journal*

of Monetary Economics, 58(5), 453–470.

<http://doi.org/10.1016/j.jmoneco.2011.05.005>

Gai, P., & Kapadia, S. (2010). Contagion in financial networks. *Proceedings of the Royal*

Society A: Mathematical, Physical and Engineering Science, 466(2120), 2401.

<http://doi.org/10.1098/rspa.2009.0410>

- Galam, S. (1986). Majority rule, hierarchical structures, and democratic totalitarianism: A statistical approach. *Journal of Mathematical Psychology*, 30, 426–434.
[http://doi.org/10.1016/0022-2496\(86\)90019-2](http://doi.org/10.1016/0022-2496(86)90019-2)
- Gentner, D. (1983). Structure mapping: A theoretical framework for analogy. *Cognitive Science*, 7(2), 155–170. [http://doi.org/10.1016/S0364-0213\(83\)80009-3](http://doi.org/10.1016/S0364-0213(83)80009-3)
- Gentner, D. (1998). Analogy. In W. Bechtel & G. Graham (Eds.), *A companion to cognitive science* (pp. 107–113). Oxford, England: Blackwell.
- Gentner, D., Brem, S., Ferguson, R. W., Markman, A. B., Levidow, B. B., Wolff, P., & Forbus, K. D. (1997). Analogical reasoning and conceptual change: A case study of Johannes Kepler. *Journal of the Learning Sciences*, 6(1), 3–40.
http://doi.org/10.1207/s15327809jls0601_2
- Georgescu-Roegen, N. (1966). *Analytical economics: Issues and problems*. Cambridge, MA: Harvard University Press.
- Georgescu-Roegen, N. (1971). *The entropy law and the economic process*. Cambridge, MA: Harvard University Press. <http://doi.org/10.2307/2231206>
- Gigerenzer, G. (1991). From tools to theories: A heuristic of discovery in cognitive psychology. *Psychological Review*, 98, 254–267.
- Gigerenzer, G. (2011). *Adaptive thinking: Rationality in the real world*. Oxford, England: Oxford University Press. <http://doi.org/10.1093/acprof:oso/9780195153729.001.0001>
- Gigerenzer, G., & Selten, R. (2001). Rethinking rationality. In G. Gigerenzer & R. Selten (Eds.), *Bounded rationality: The adaptive toolbox* (Vol. 1, pp. 1–12). Cambridge, MA: MIT Press.
- Gigerenzer, G., Swijtink, Z., Porter, T., Daston, L., Beatty, J., & Krüger, L. (1989). *The empire of chance: How probability changed science and everyday life*. Cambridge, England:

Cambridge University Press.

Gorelik, G. (1975). Reemergence of Bogdanov's tektology in Soviet studies of organization.

Academy of Management Journal, 18(2), 345–357. <http://doi.org/10.2307/255536>

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., ... DeAngelis, D. L.

(2006). A standard protocol for describing individual-based and agent-based models.

Ecological Modelling, 198(1-2), 115–126.

<http://doi.org/10.1016/j.ecolmodel.2006.04.023>

Grimm, V., & Calabrese, J. M. (2011). What is resilience? A short introduction.

Understanding Complex Systems, 2011, 3–13. [http://doi.org/10.1007/978-3-642-](http://doi.org/10.1007/978-3-642-20423-4_1)

20423-4_1

Guimerà, R., Mossa, S., Turttschi, A., & Amaral, L. A. N. (2005). The worldwide air

transportation network: Anomalous centrality, community structure, and cities' global

roles. *Proceedings of the National Academy of Sciences of the United States of America*,

102(22), 7794–7799. <http://doi.org/10.1073/pnas.0407994102>

Gunderson, L. H. (2000). Ecological resilience in theory and application. *Ecology and*

Systematics, 31, 425–439. <http://doi.org/10.1146/annurev.ecolsys.31.1.425>

Haldane, A., & Madouros, V. (2012). The dog and the Frisbee. The Bank of England. In

Speech given at the Federal Reserve Bank of Kansas City's 36th economic policy

symposium, "The Changing Policy Landscape", Jackson Hole, Wyoming (Vol. 31).

Retrieved from

<http://www.bankofengland.co.uk/publications/Pages/speeches/default.aspx>

Haldane, A., & May, R. M. (2011). Systemic risk in banking ecosystems. *Nature*, 469(7330),

351–355. <http://doi.org/10.1038/nature09659>

Hammerstein, P. (2001). Evolutionary adaptation and the economic concept of bounded

- rationality—A dialogue. In G. Gigerenzer & R. Selten (Eds.), *Bounded rationality: The adaptive toolbox* (pp. 71–81). Cambridge, MA: MIT Press.
- Hayek, F. A. (1971). Nature vs. nurture once again. *Encounter*, 36, 81–83.
- Hesse, M. B. (1966). *Models and analogies in science*. Notre Dame, IN: University of Notre Dame Press. <http://doi.org/10.1017/CBO9781107415324.004>
- Hodgson, G. M. (1997). Economics and the return to Mecca: The recognition of novelty and emergence. *Structural Change and Economic Dynamics*, 8(4), 399–412.
[http://doi.org/10.1016/S0954-349X\(96\)00073-2](http://doi.org/10.1016/S0954-349X(96)00073-2)
- Hodgson, G. M. (1998). Evolutionary economics. In J. B. Davis, D. W. Hands, & U. Mäki (Eds.), *The handbook of economic methodology* (pp. 160–165). Cheltenham, England: Elgar.
- Hodgson, G. M., & Knudsen, T. (2006). Why we need a generalized Darwinism, and why generalized Darwinism is not enough. *Journal of Economic Behavior and Organization*, 61(1), 1–19. <http://doi.org/10.1016/j.jebo.2005.01.004>
- Holland, J. H. (1992a). *Adaptation in natural and artificial systems*. Ann Arbor, MI: University of Michigan Press.
- Holland, J. H. (1992b). Complex adaptive systems. *Daedalus*, 121(1), 17–30.
<http://doi.org/10.2307/20025416>
- Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, 4(1), 1–23. <http://doi.org/10.1146/annurev.es.04.110173.000245>
- Holling, C. S. (2001). Understanding the complexity of economic, ecological, and social systems. *Ecosystems*, 4(5), 390–405. <http://doi.org/10.1007/s10021-00>
- Holling, C. S., & Gunderson, L. H. (2002). Resilience and adaptive cycles. In L. H. Gunderson & C. S. Holling (Eds.), *Panarchy: Understanding transformations in human and natural systems* (pp. 25–62). Washington, DC: Island Press.

- Holt, R., Rosser, B., & Colander, D. (2011). The complexity era in economics. *Review of Political Economy*, 23(3), 357–369. <http://doi.org/10.1080/09538259.2011.583820>
- Holton, G. (1988). *Thematic origins of scientific thought: Kepler to Einstein*. Cambridge, MA: Harvard University Press. (Original work published 1973).
- Holton, G. (1996). The role of themata in science. *Foundations of Physics*, 26(4), 453–465.
- Holyoak, K. J., & Thagard, P. (1996). *Mental leaps: Analogy in creative thought*. Cambridge, MA: MIT Press. http://doi.org/10.1207/s15327868ms1201_8
- Hutchinson, J. M. C., & Gigerenzer, G. (2005). Connecting behavioural biologists and psychologists: Clarifying distinctions and suggestions for further work. *Behavioural Processes*, 69(2), 159–163. <http://doi.org/10.1016/j.beproc.2005.02.020>
- Ingrao, B., & Israel, G. (2000). *The invisible hand: Economic equilibrium in the history and science*. Cambridge, MA: MIT-Press.
- Jaffe, W. (1965). *Correspondence of Léon Walras and related papers*. Amsterdam, the Netherlands: North-Holland.
- Janssen, M. A., Schoon, M. L., Ke, W., & Börner, K. (2006). Scholarly networks on resilience, vulnerability and adaptation within the human dimensions of global environmental change. *Global Environmental Change*, 16(3), 240–252. <http://doi.org/10.1016/j.gloenvcha.2006.04.001>
- Jevons, W. S. (1888). *The theory of political economy*. London, England: Macmillan. (Original work published in 1971).
- Jones, K. D., & Nguyen, C. (2005). Increased concentration in banking: Megabanks and their implications for deposit insurance. *Financial Markets, Institutions & Instruments*, 14(1), 1–42.
- Jones, R. M., & Langley, P. (2005). A constrained architecture for learning and problem

- solving. *Computational Intelligence*, 21(4), 480–502. <http://doi.org/10.1111/j.1467-8640.2005.00283.x>
- Jovanovic, F., & Schinckus, C. (2013). The emergence of econophysics: A new approach in modern financial theory. *History of Political Economy*, 45(3), 443–474.
<http://doi.org/10.1215/00182702-2334758>
- Kalaitzidakis, P., Mamuneas, T. P., & Stengos, T. (2011). An updated ranking of academic journals in economics. *Canadian Journal of Economics*, 44(4), 1525–1538.
<http://doi.org/10.1111/j.1540-5982.2011.01683.x>
- Kalaitzidakis, P., Stengos, T., & Mamuneas, T. P. (2003). Rankings of academic journals and institutions in economics. *Journal of the European Economic Association*, 1(6), 1346–1366. <http://doi.org/10.1162/154247603322752566>
- Kaldor, N. (1940). A model of the trade cycle. *The Economic Journal*, 50(197), 78–92.
<http://doi.org/10.2307/2225740>
- Kelly, M., & Ó Gráda, C. (2000). Market contagion: evidence from the panics of 1854 and 1857. *American Economic Review*, 90(5), 1110–1124.
- Kendall, M. G., & Hill, A. B. (1953). The analysis of economic time-series Part I: Prices. *Journal of the Royal Statistical Society*, 116(1), 11–34. <http://doi.org/10.2307/2980947>
- Kirman, A. (1992). Whom or what does the representative agent represent? *Journal of Economic Perspectives*, 6(2), 117–136.
- Klamer, A., & Leonard, T. C. (1994). So what's an economic metaphor? In P. Mirowski (Ed.), *Natural images in economic thought: Markets read in tooth and claw* (pp. 20–51). Cambridge, England: Cambridge University Press.
- Klimek, P., Poledna, S., Farmer, J. D., & Thurner, S. (2015). To bail-out or to bail-in? Answers from an agent-based model. *Journal of Economic Dynamics and Control*, 50, 144–154.

<http://doi.org/10.1016/j.jedc.2014.08.020>

Knight, F. H. (1921). *Risk, uncertainty, and profit*. Boston, MA: Houghton Mifflin.

Krugman, P. (2009, September 2). How did economists get it so wrong? *New York Times*.

Retrieved from <http://www.nytimes.com>

Kuhn, T. (1962). *The structure of scientific revolutions*. Chicago, IL: University of Chicago

Press. <http://doi.org/10.1046/j.1440-1614.2002.t01-5-01102a.x>

Kuhn, T. (1979). Metaphor in science. In A. Ortony (Ed.), *Metaphor and thought* (pp. 409–419). Cambridge, England: Cambridge University Press.

Lane, D. (2006). Hierarchy, complexity, society. In D. Pumain (Ed.), *Hierarchy in natural and social sciences* (pp. 81–119). Dordrecht, The Netherlands: Springer.

http://doi.org/10.1007/1-4020-4127-6_5

Langley, P., & Jones, R. M. (1988). A computational model of scientific insight. In R. J.

Sternberg (Ed.), *The nature of creativity: Contemporary psychological perspectives* (pp. 177–201). New York, NY: Cambridge University Press.

Langton, C. G. (1986). Studying artificial life with cellular automata. *Physica D: Nonlinear Phenomena*, 22(1-3), 120–149. [http://doi.org/10.1016/0167-2789\(86\)90237-X](http://doi.org/10.1016/0167-2789(86)90237-X)

Lichtenstein, B. B., & McKelvey, B. (2011). Four types of emergence: A typology of complexity and its implications for a science of management. *International Journal of Complexity in Leadership and Management*, 1(4), 339–378.

<http://doi.org/10.1504/IJCLM.2011.046439>

Lillo, F., Mike, S., & Farmer, J. D. (2005). Theory for long memory in supply and demand. *Physical Review E*, 71(6). <http://doi.org/10.1103/PhysRevE.71.066122>

Liu, J., Dietz, T., Carpenter, S. R., Alberti, M., Folke, C., Moran, E., ... Taylor, W. W. (2007). Complexity of coupled human and natural systems. *Science*, 317(5844), 1513–1516.

<http://doi.org/10.1126/science.1144004>

Lo, A. W. (1991). Long-term memory in stock market prices. *Econometrica*.

Lo, A. W., & Mueller, M. T. (2010). WARNING: Physics envy may be hazardous to your wealth! *Journal of Investment Management*, 8, 13–63.

<http://doi.org/10.2139/ssrn.1563882>

Lorenz, H.-W. (1993). *Nonlinear dynamical economics and chaotic motion*. Berlin, Germany: Springer.

Lowe, A. (1975). Adam Smith's system of equilibrium growth. In A. S. Skinner & T. Wilson (Eds.), *Essays on Adam Smith* (pp. 415–425). Oxford, England: Clarendon Press.

Lux, T. (2008). *Applications of statistical physics in finance and economics* (Kiel Working Paper). Kiel, Germany: Kiel Institute for the World Economy. Retrieved from <http://econpapers.repec.org/RePEc:kie:kieliw:1425>

Mandelbrot, B. (1963). The variation of certain speculative prices. *The Journal of Business*, 36(4), 394–419. <http://doi.org/10.1086/294632>

Mandelbrot, B., & Hudson, R. L. (2010). *The (mis)behavior of markets: A fractal view of financial turbulence*. London, England: Profile Books.

Mantegna, R. N., & Stanley, H. E. (2000). *An introduction to econophysics*. Cambridge, England: Cambridge University Press. <http://doi.org/10.1063/1.1341926>

Markowitz, H. M. (1952). Portfolio selection. *The Journal of Finance*, 7, 77–91. <http://doi.org/10.1111/j.1540-6261.1952.tb01525.x>

Marshall, A. (1920). *Principles of economics*. London, England: Macmillan (Original work published 1890). <http://doi.org/10.1057/9781137375261>

Maxwell, J. C. (1868). On governors. *Proceedings of the Royal Society of London*, 16, 270–283.

- Maxwell, J. C. (1990). Abstract of paper "On Faraday's lines of force." In P. M. Harman (Ed.), *The scientific letters and papers of James Clerk Maxwell: 1846-1862*. Cambridge, England: Cambridge University Press. (Original work published in 1855).
- May, R. M., Levin, S. A., & Sugihara, G. (2008). Complex systems: ecology for bankers. *Nature*, 451(7181), 893–895. <http://doi.org/10.1038/451893a>
- McCann, K., Hastings, A., & Huxel, G. R. (1998). Weak trophic interactions and the balance of nature. *Nature*, 395(6704), 794–798. <http://doi.org/10.1038/27427>
- McCloskey, D. N. (1985). *The rhetoric of economics*. Madison, WI: University of Wisconsin Press. <http://doi.org/10.2307/2071183>
- McClure, M. T. (2001). *Pareto, economics and society: The mechanical analogy*. London, England: Routledge.
- Meadows, D. H., Meadows, D. L., Randers, J., & Behrens, W. W. (1972). *The limits to growth: A report for the Club of Rome's project on the predicament of mankind*. New York, NY: Universe Books. <http://doi.org/10.1111/j.1752-1688.1972.tb05230.x>
- Meder, B., Le Lec, F., & Osman, M. (2013). Decision making in uncertain times: what can cognitive and decision sciences say about or learn from economic crises? *Trends in Cognitive Sciences*, 17(6), 257–260. <http://doi.org/10.1016/j.tics.2013.04.008>
- Merton, R. C. (1973). Theory of rational option pricing. *The Bell Journal of Economics and Management Science*, 4(1), 141–183. <http://doi.org/10.2307/3003143>
- Miller, J. G. (1972). Living systems: the organization. *Behavioral Science*, 17(1), 1–82. <http://doi.org/10.1002/bs.3830170102>
- Minoiu, C., & Reyes, J. A. (2013). A network analysis of global banking: 1978–2010. *Journal of Financial Stability*, 9(2), 168–184. <http://doi.org/10.1016/j.jfs.2013.03.001>
- Mirowski, P. (1989). *More heat than light: Economics as social physics, physics as nature's*

- economics*. Cambridge: Cambridge University Press.
- <http://doi.org/10.1017/S0266267100000559>
- Mirowski, P. (1990). From Mandelbrot to chaos in economic theory. *Southern Economic Journal*, 57, 289–307.
- Moorhouse, J. C. (1978). The mechanistic foundations of economic analysis. *Reason Papers: A Journal of Interdisciplinary Normative Studies*, 1(4), 49–67.
- Morgan, M. (2012). *The world in the model: How economists work and think*. Cambridge, England: Cambridge University Press.
- Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Cambridge, MA. <http://doi.org/10.2307/2232409>
- Nier, E., Yang, J., Yorulmazer, T., & Alentorn, A. (2007). Network models and financial stability. *Journal of Economic Dynamics and Control*, 31(6), 2033–2060.
- <http://doi.org/10.1016/j.jedc.2007.01.014>
- Nozer, D. S., & Wilson, S. (2008). The mathematics of risk and reliability: A select history. In E. L. Melnick & B. S. Everitt (Eds.), *Encyclopedia of quantitative risk analysis and assessment* (pp. 1054–1062). Chichester, UK: John Wiley and Sons.
- <http://doi.org/10.1002/97801470661596>
- O'Neill, R. V. (2001). Is it time to bury the ecosystem concept? (With full military honors, of course!). *Ecology*, 82(12), 3275–3284. <http://doi.org/10.2307/2680151>
- Odum, E. P. (1953). *Fundamentals of ecology*. Philadelphia, PA: Saunders.
- Odum, H. T. (1971). *Environment, power, and society*. New York, NY: Wiley.
- Palmer, R. G., Arthur, W. B., Holland, J. H., LeBaron, B., & Tayler, P. (1994). Artificial economic life: A simple model of a stock market. *Physica D*, 75, 264–274.
- Poincaré, H. (1887). Sur les hypothèses fondamentales de la géométrie. *Bulletin de La*

- Société Mathématique de France*, 15, 203–216.
- Poledna, S., Molina-Borboa, J. L., Martínez-Jaramillo, S., van der Leij, M., & Thurner, S. (2015). The multi-layer network nature of systemic risk and its implications for the costs of financial crises. *Journal of Financial Stability*, 20, 70–81.
- Poledna, S., & Thurner, S. (2014). *Elimination of systemic risk in financial networks by means of a systemic risk transaction tax* (arXiv preprint arXiv:1401.8026 [q-fin.RM]).
- Prigogine, I., & Defay, R. (1954). *Treatise on thermodynamics: Based on the methods of Gibbs and De Donder*. London, England: Longmans, Green.
- Prigogine, I., & Stengers, I. (1984). *Order out of chaos: Man's new dialogue with nature*. London, England: Fontana.
- Prokhorov, A. B. (2001). Nonlinear dynamics and chaos theory in economics: A historical perspective. *Techn. Ber*, 1–28.
- Ricotta, C., & Marignani, M. (2007). Computing β -diversity with Rao's quadratic entropy : A change of perspective. *Diversity and Distributions*, 13(2), 237–241.
<http://doi.org/10.1111/j.1472-4642.2006.00316.x>
- Rosser, B. (1999). On the complexities of complex economic dynamics. *Journal of Economic Perspectives*, 13(4), 169–192. <http://doi.org/10.1257/jep.13.4.169>
- Ruth, M. (1996). Evolutionary economics at the crossroads of biology and physics. *Journal of Social and Evolutionary Systems*, 19(2), 125–144. [http://doi.org/10.1016/S1061-7361\(96\)90021-1](http://doi.org/10.1016/S1061-7361(96)90021-1)
- Salthe, S. N. (1985). *Evolving hierarchical systems: Their structure and representation*. New York, NY: Columbia University Press.
- Salvucci, D. D., & Anderson, J. R. (2001). Integrating analogical mapping and general problem solving: The path-mapping theory. *Cognitive Science*, 25(1), 67–110.

[http://doi.org/10.1016/S0364-0213\(00\)00035-5](http://doi.org/10.1016/S0364-0213(00)00035-5)

Samuelson, P. A. (1947). *Foundations of economic analysis*. Cambridge, MA: Harvard University Press.

Samuelson, P. A. (1960). Structure of a minimum equilibrium system. In *Essays in economics and econometrics: A volume in honor of Harold Hotelling* (pp. 1–33). Chapel Hill, NC: University of North Carolina Press.

Samuelson, P. A. (1986). *The collected scientific papers of Paul A. Samuelson*. (K. Crowley, Ed.). Cambridge, MA: MIT Press.

Samuelson, P. A. (1998). How foundations came to be. *Journal of Economic Literature*, 36(3), 1375–1386.

Scheffer, M., Bascompte, J., Brock, W. A., Brovkin, V., Carpenter, S. R., Dakos, V., ... Sugihara, G. (2009). Early-warning signals for critical transitions. *Nature*, 461(7260), 53–59.
<http://doi.org/10.1038/nature08227>

Scheffer, M., Carpenter, S. R., Lenton, T. M., Bascompte, J., Brock, W., Dakos, V., ... Vandermeer, J. (2012). Anticipating critical transitions. *Science*, 338(6105), 344–348.
<http://doi.org/10.1126/science.1225244>

Schelling, T. C. (1971). Dynamic models of segregation. *The Journal of Mathematical Sociology*, 1(2), 143–186. <http://doi.org/10.1080/0022250X.1971.9989794>

Schumpeter, J. A. (1934). *The theory of economic development*. Cambridge, MA: Harvard University Press. (Original work published 1912).

Schumpeter, J. A. (1994). *The history of economic analysis*. London, England: Routledge Allen & Unwin. (Original work published 1954).

Sebba, G. (1953). The development of the concepts of mechanism and model in physical science and economic thought. *American Economic Review*, 43(2), 259–268.

- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425–442. <http://doi.org/10.2307/2329297>
- Simon, H. A. (1947). *Administrative behavior: A study of decision making processes in administrative organizations*. New York, NY: Macmillan.
- Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1), 99–118. <http://doi.org/10.2307/1884852>
- Simon, H. A. (1962). The architecture of complexity. *American Philosophical Society*, 106, 467–482.
- Simon, H. A., & Newell, A. (1971). Human problem solving: The state of the theory in 1970. *American Psychologist*, 26, 145–159.
- Smith, A. (1822). *Essays on philosophical subjects*. In *The whole works of Adam Smith* (Vol. 5). London: J. Richardson. (Original work published in 1795).
- Smith, E., & Foley, D. K. (2008). Classical thermodynamics and economic general equilibrium theory. *Journal of Economic Dynamics and Control*, 32(1), 7–65. <http://doi.org/10.1016/j.jedc.2007.01.020>
- Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, 70(1), 65–94. <http://doi.org/10.2307/1884513>
- Thoben, H. (1982). Mechanistic and organistic analogies in economics reconsidered. *Kyklos*, 35, 292–306.
- Thomas, B. (1991). Alfred Marshall on economic biology. *Review of Political Economy*, 3(1), 1–14.
- Turner, S., & Poledna, S. (2013). DebtRank-transparency: controlling systemic risk in financial networks. *Scientific Reports*, 3, 1888. <http://doi.org/10.1038/srep01888>
- Todd, P. M., Gigerenzer, G., & the ABC Research Group. (2012). *Ecological rationality:*

- Intelligence in the world* (Vol. 34). New York, NY: Oxford University Press.
- <http://doi.org/10.1016/j.joep.2012.10.007>
- Tonkiss, F. (2009). Trust, confidence and economic crisis. *Intereconomics*, 44(4), 196–202.
- <http://doi.org/10.1007/s10272-009-0295-x>
- Twu, P., Mostofi, Y., & Egerstedt, M. (2014). A measure of heterogeneity in multi-agent systems. In *Proceedings of the American Control Conference* (pp. 3972–3977).
- <http://doi.org/10.1109/ACC.2014.6858632>
- Uslaner, E. M. (2010). Trust and the economic crisis of 2008. *Corporate Reputation Review*, 13(2), 110–123. <http://doi.org/10.1057/crr.2010.8>
- van den Bergh, J. C., & Verbruggen, H. (1999). Spatial sustainability, trade and indicators: An evaluation of the “ecological footprint.” *Ecological Economics*, 29(1), 61–72.
- [http://doi.org/10.1016/S0921-8009\(99\)00032-4](http://doi.org/10.1016/S0921-8009(99)00032-4)
- Van Langevelde, F., Van De Vijver, C. A. D. M., Kumar, L., Van De Koppel, J., De Ridder, N., Van Andel, J., ... Rietkerk, M. (2003). Effects of fire and herbivory on the stability of savanna ecosystems. *Ecology*, 84(2), 337–350. [http://doi.org/10.1890/0012-9658\(2003\)084\[0337:EOFAHO\]2.0.CO;2](http://doi.org/10.1890/0012-9658(2003)084[0337:EOFAHO]2.0.CO;2)
- Veblen, T. (1898). Why is economics not an evolutionary science? *Quarterly Journal of Economics*, 12, 373–397.
- von Bertalanffy, L. (1950). The theory of open systems in physics and biology. *Science*, 111(1), 23–29. <http://doi.org/10.1126/science.111.2872.23>
- Walker, B., Holling, C. S., Carpenter, S. R., & Kinzig, A. (2004). Resilience, adaptability and transformability in social-ecological systems. *Ecology and Society*, 9(2). Retrieved from <http://www.ecologyandsociety.org/vol9/iss2/art5/>
- Walras, L. (1909). Economique et mécanique. *Bulletin de La Société Vaudoise de Sciences*

Naturelles., 45, 313–325.

Walras, L. (1954). *Elements of pure economics* (W. Jaffé, Trans.). London, England: Allen & Unwin. (Original work published in 1874).

Walras, L. (1987). Une Branche Nouvelle de la Mathematique. In A. Walras, L. Walras, & P. Dockès (Eds.), *Oeuvres Economiques Completes* (pp. 291–329). Paris, France: Economica. (Original work published in 1927).

Weaver, W. (1948). Science and complexity. *American Scientist*, 36(4), 536–544.

<http://doi.org/yes>

Weidlich, W. (1971). The statistical description in polarization phenomena in society. *British Journal of Mathematical and Statistical Psychology*, 24(2), 251–266.

Weintraub, E. R. (2007). Neoclassical economics. In S. R. Clegg & J. R. Bailey (Eds.), *The concise encyclopedia of economics*. <http://doi.org/10.4135/9781412956246.n329>

Wiener, N. (1948). *Cybernetics*. Paris, France: Hermann.

Witt, U. (1996). Innovations, externalities and the problem of economic progress. *Public Choice*, 89(1-2), 113–130. <http://doi.org/10.1007/BF00114282>

Witt, U. (2008). What is specific about evolutionary economics? *Journal of Evolutionary Economics*, 18(5), 547–575. <http://doi.org/10.1007/s00191-008-0107-7>

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